# Sensor technologies and fall prevention

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# SENSOR TECHNOLOGIES AND FALL PREVENTION

Sensor technologies to assess fall risk in long-term care residents with dementia and gait in healthy older adults

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# Contents

# CHAPTER 1

# General introduction

# General introduction



Healthy aging refers to maintaining physical and cognitive health, avoiding disease and disability, and remaining active and independent. Unfortunately, not all of the 3 million adults aged 65 and over in The Netherlands (17% of the total population) enjoy healthy aging [1,2]. Natural aging is associated with a decline in physical function and cognition and has serious consequences for mobility, fall risk, quality of life, health care dependence, and mortality [3,4]. The aging population is a growing concern for today's society. The high cost of fall-related injuries and long-term care for the elderly present a tremendous social and financial burden for family members [5]. Maintaining independence, autonomy, and quality of life as long as possible is of utmost importance for old adults, their families, and caregivers. Under the guise of 'prevention is better than curing' a variety of prevention methods aims to improve or maintain physical and cognitive function in old adults. Prevention strategies can be divided into two approaches: 1) prevention by real-time monitoring of individuals to detect high-risk situations and provide signals for immediate care, and 2) prevention through prolonged intervention, such as exercise training, medication review, and educational programs [6]. Before implementing appropriate prevention methods for individuals, one must accurately determine whether there is a high risk for a fall or mobility loss. Emerging technological solutions may lead to more effective and tailored prevention based on the ability to detect small but essential changes prior to an overt manifestation of mobility impairment such as a fall or inability to walk.

The present thesis addressed two different, yet conceptually interlinked, prevention issues. The concept that links the two thesis parts is prevention. One aim was to identify situations that can lead to falls in highly vulnerable psychogeriatric patients. The second aim was to detect signs of deterioration in gait and dynamic balance in still healthy old adults who might fall later in life. Thus, part one describes the search for and development of a fall prevention sensor system in a long-term care facility. The target population for this first project was frail elderly persons with dementia who were at high risk for falling. These patients lived in a psychogeriatric ward of a long-term care facility. In this vulnerable group, falls occur frequently and are associated with substantial physical, psychological and financial consequences. The aim of this project was to assess the circumstances of falls and evaluate the possibility of monitoring residents with a sensor-based system to detect high fall risk situations and provide feedback to the health care staff for immediate care. The project took into account the experiences, attitudes, and expectations of health care staff (end-users) toward a fall prevention sensor system during system development. The second part of this thesis originates from the request of clinical practitioners and geriatric departments to develop a small, low-cost, user-friendly, and accurate device to detect early markers of decline in balance and gait instability, so as to enable timely and targeted interventions to slow or even stop the decline process. Considering the tremendous mobile technology advances and the increased number of smart device users, we investigated the validity and reliability of the built-in, tri-axial accelerometer in the iPod Touch to record gait and balance capacity. Furthermore, the relationship between gait variables derived from the accelerometer signal and age was examined to provide a frame of reference for gait pattern changes due to natural aging.

## Technology-based fall risk assessment in long-term care residents with dementia

### *Falls in long-term care facilities*

In The Netherlands, 165,000 adults older than 65 live in long-term care facilities [2]. People living in long-term care facilities are most often diagnosed with cognitive impairment or severe physical limitations. Although the health problems in this population vary widely, these people have in common that they can no longer live independently. Long-term care facilities face the challenge of providing care and facilitating a safe and comfortable stay, while maintaining optimal autonomy and quality of life. Unfortunately, a fall can ruin previously stable health instantaneously. Cognitive problems in combination with physical limitations of long-term care residents increase fall risk. Consequently (and unfortunately), falls occur frequently in long-term care facilities. These falls lead to physical consequences (e.g., injuries, open wounds, fractures, and brain damage) and psychosocial consequences (e.g., loss of confidence, anxiety, and depression) [7–9]. After a fall, old adults become more dependent, with an ensuing reduction in quality of life. Every year 7,700 long-term care residents aged 65 years or older visit a hospital emergency department in The Netherlands after an accident, 95% of which are due to falls [9]. On average, the health care-related costs are €13,000 per accident, a significant financial burden compared with the average annual per capita costs of €8,400 for the total population of old adults aged 65 years and over. Almost half of residents experiencing an accident require hospitalization, of whom 60% experienced a hip fracture. Additionally, 510 residents die each year as a result of accidents in long-term care facilities. Although those numbers are alarming, these costs most likely underestimate the real costs of fall-related injuries in long-term care residents because these numbers only include accidents registered in Dutch hospital emergency departments [9]. To reduce the number of falls and fall-related injuries in long-term care residents with dementia, effective fall prevention is necessary.

### *Fall prevention in long-term care facilities*

There are multiple fall prevention programs specifically developed for long-term care residents. These interventions include: balance and mobility training, behavior-changing interventions, vitamin D and calcium supplementation, and programs combining multiple intervention methods [10–12]. Unfortunately, only a few fall prevention programs have been successful. The recipe for a successful fall prevention program seems to be a multifaceted program consisting of resident-specific strategies (e.g., medication review, risk assessment), group-specific strategies (e.g., exercise sessions) and general intervention strategies (e.g., staff education, environmental modifications) [12]. However, these fall prevention programs are rarely implemented in institutions because such programs are labor- and time-intensive for health care staff [13,14]. Additionally, the cognitive tasks of learning fall strategies, balance and mobility training, or recognizing and avoiding high fall risk situations are difficult for residents with dementia. Because prevention through intervention has had limited success for long-term care residents, prevention by individual monitoring seems to be a suitable alternative. Although health care staff cannot continually monitor residents, technology-based solutions can be used to assist in monitoring residents and detecting adverse events, including falls. Fall detection devices are available, including accelerometers detecting falls based on the magnitude of acceleration signals or camera systems identifying someone lying still on the ground for several minutes [15–17]. However, to avoid fall consequences, a high fall risk situation needs to be detected prior to the fall occurrence. Because more than 50% of all falls occur in residents' bedrooms [8], bed sensors have been introduced. The alarm systems, using infrared or pressure sensors, notify the health care staff when a resident is getting out of bed and assistance is needed [18–23]. However, bed alarm systems are freedom-restricting, and circumstances and locations of falls are not fixed. Falls occur due to a wide range of circumstances (e.g., restlessness, medication, cognitive status) that produce dynamic risk factors that change over time and differ between persons [24–26]. Therefore, monitoring is required of multiple events and locations with individual risk detection. Recent developments in technology, including sensor miniaturization, multiple sensor use, data transmission, and data processing make it possible to continually monitor movement, human physiology, and behavior for longer periods. Data processing enables early and accurate detection of abnormalities in behavior or movements, as well as identification of circumstances immediately preceding falls for individual residents. Personalized fall risk decision-making models can be developed to recognize situations and events that increase fall risk. The decision-making models can learn over time based on accumulated data and can adapt to changes in resident status.

The INTERREG IV A 'Telemedicine & Personalized Care – project fall prevention' aimed to develop a smart fall prevention sensor system that automatically identifies increased fall risk in long-term care residents with dementia. After detection of a high fall risk situation, the system is designed to rapidly alert health care staff. This alert enables tailored care and increases the effectiveness and quality of health care. Because this project requires expertise in various disciplines, a multidisciplinary collaboration between companies integrating technology and processing large datasets, clinical settings, and knowledge institutions was initiated.

*Sensors for fall prevention*

The first step in developing a reliable and accurate system is to evaluate the current state of prevention technologies and to determine the conditions for a successful fall prevention technology. There is a broad range of sensors available to detect specific events (such as standing up from a chair or leaving a certain room) and alert the health care staff. Event detection can be based on cameras, infrared sensors, inertial sensors, global positioning system (GPS) or pressure sensors [27–30]. The sensors can be divided into two main categories: wearable and non-wearable sensors. Wearable sensors can be placed in shoes, clothes, around the wrist in a bracelet, or hanging as a necklace; therefore, they have the advantage of not being fixed to one specific location. However, the problem with wearable sensors is that residents with cognitive impairment suffering from confusion or physical inconveniences may simply remove shoes, clothes, or a bracelet [22,31] This removal results in inaccurate monitoring or absence of monitoring.

Non-wearable sensors seem to be a good alternative for long-term care residents with dementia. In the Ambient Assisted Living (AAL) project, the surveillance system 'Rosetta,' was developed to monitor old adults with dementia living independently [32,33]. A sensor system based on cameras, infrared movement detectors, a bed mat, smoke alarms, and magnetic door sensors recorded the lifestyle of community-dwelling old adults with dementia. The data recorded in the first two weeks were used to define the normal daily routine. Afterwards, deviations from the normal daily routine such as wandering during the night, changing eating and drinking patterns, and bathroom use could be identified. Unfortunately, this monitoring system is not suitable for fall prevention in intramural care facilities because it cannot deal with multiple persons in one room and because it detects fall incidents instead of predicting them. Nevertheless, owing to delays in, and in some cases avoidance of, institutionalization of the participating old adults, this project demonstrates the high potential of non-wearable sensors in combination with a decision-making model to use as a monitoring system.

*Fall risk factors*

The development of an effective fall prevention system with a decision-making model requires information concerning factors that lead to falls. Factors contributing to falls in long-term care residents with dementia include: cognitive impairment, fall history, incontinence, polypharmacy, use of antidepressants and benzodiazepines, gait disturbances, behavior problems, functional dependence, anxiety, poor attention and orientation, urinary infection, slippery floors, and poor lightning [34–39]. Although we know that when more fall risk factors are simultaneously present fall risk increases, the relationship between risk factors and the association with fall incidents is still unknown. Complex interactions among fall risk factors underlie many falls [40]. Some factors may reinforce each other, whereas other factors may have counteracting effects. Understanding the relationship between risk factors and the association with falls could contribute to an accurate fall risk decision-making model. Monitoring residents and measuring multiple factors known to be involved in falls may enable health care staff to intervene and reduce fall potential.



It is unlikely that a standard fall risk decision-making model will fit for all long-term care residents with dementia. Long-term care residents with dementia represent a heterogeneous patient group. These patients experience a range of cognitive dysfunction combined with diverse co-morbidities, frailty markers, and medication use. Each resident would have a unique combination of factors predisposing to falls. Therefore, a personalized fall risk decision-making model is needed. Moreover, physical and cognitive function may change rapidly in long-term care residents. For example, a resident who is independent one day can become wheelchair-dependent within weeks. Such changes require a dynamic fall risk decision-making model that can adapt to ever-changing individual patient living and medical conditions.

*User involvement*
Introducing technology in health care institutions significantly impacts the work of health care staff and changes daily routines. A large number of projects has failed to introduce technology into clinical practice, not due to flawed technology, but rather due to the lack of involvement of health care staff (end-users) throughout the technology development and implementation. Consequently, technology developed without user involvement remains unused. The user-as-designer approach includes user involvement early and continuously during the design process [41]. The user is a part of the development team that finds solutions to address the needs and values of the health care staff and their patients. The user is the expert concerning the requirements and demands from the clinical practice, whereas the technicians and data analysts know the opportunities and the possibilities of technology use. User involvement promotes a sense of empowerment and contributes to more efficient and effective solutions that may work better than solutions conceived without stakeholder input. Successful development and implementation can increase ease of use and learning, adoption, and satisfaction of users.

***Objectives***
The final goal of the INTERREG IV A project was the development and implementation of a smart fall prevention sensor system using wireless integrated video and bed mats (pressure sensors) to continuously monitor resident movements and physical status in his living surroundings. At the same time, biomarkers, such as heart rate, body temperature, and blood sugar levels, as well as chart data on behavioral and medical status are monitored and combined with the sensor data. All available information is then integrated and interpreted in an effort to generate a multivariate data analysis-based personal, decision-making model. The result is a dynamic system that can learn over time and adapt the decision models according to the events and other changes.

The first steps to develop this technological solution for fall prevention in long-term care residents with dementia are described in the present thesis. The first three objectives were to:

1) review the effectiveness of fall prevention technologies used in intramural care facilities with respect to fall rate and fall-related injuries, false alarms, and user experience;
2) determine fall rate, fall-related injuries, and circumstances of these falls in long-term care residents with dementia. Additionally, the relationship between patient characteristics (classified into seven domains: demographics, activities of daily living (ADL) performance, mobility, cognition and behavior, vision and hearing, medical conditions, and medication use) and fall rate was examined;
3) assess the attitude of caregivers toward fall prevention, fall prevention technology, and policy making.

## Technology-based gait assessment in healthy adults

### *Changes due to aging*

Natural aging is characterized by skin wrinkles, gray hair or baldness, slowness, rigidity, sarcopenia, vision and hearing impairments, and forgetfulness. Though the visible changes due to aging may appear late in adulthood, the onset of the aging process starts in early adolescence. The progressive deterioration of muscle mass and muscle function starts around the age of 30 [3]. Until the age of 50, there is moderate decline of muscle mass of about 10%. After the age of 50 the decline accelerates, leading to an annual decrease of up to 2% [42]. Additionally, cognitive processes change while aging, whereby reaction time increases by 25% between ages 20 and 60 [3]. Natural aging is inescapable; strength, range of motion, cognition, reaction time, proprioception, and the sensory motor system will deteriorate over the years and will more or less influence mobility, learning capacities, functional abilities, activities of daily living, and quality of life [42,3,43].

As a consequence of natural aging, postural control and gait will change as persons grow older. However, gait changes can also occur as a result of age-related neurologic and non-neurologic disorders [44–47]. In fact, immobility, frailty, falls, dementia, institutionalization, and even early death in old adults have been associated with early detected gait abnormalities [48–51]. Identifying gait abnormalities at an early stage and monitoring gait changes over time might enable timely identification of abnormal decline and offer the opportunity for early and personalized interventions to reverse or slow the progression of balance and mobility impairments and disease evolution.

### *Gait and balance assessment*

Gait speed is the most commonly used gait parameter to discriminate old adults with certain pathologies from their healthy peers. Gait speed is reduced in Parkinson’s disease, multiple sclerosis, dementia, frail old adults, and fallers [44,46,52–55]. Although decreased gait speed can be considered as deviation from natural aging, this parameter is not specific and therefore not appropriate to detect early changes in gait quality. Additionally, tests especially developed to assess gait and balance ability often use a threshold to categorize individuals (e.g., “at risk” or “not at risk”). For example, the Timed Up and Go (TUG) is an easy and quick test to perform; however, there is growing evidence indicating the limited predictive value of the stated threshold to distinguish fallers from non-fallers [56]. Additionally, many functional tests suffer from ceiling effects and do not address changes due to balance and mobility [56,57]. Therefore, a sensitive and more specific gait assessment test is necessary, including a reference frame of gait changes occurring during natural aging, to identify old adults as soon as gait abnormalities emerge.

*Sensor devices for gait assessment*

Currently, various sensors are available to quantitatively and objectively assess gait and postural ability. These devices range from laboratory-bound sensors (e.g., Optotrak and Vicon motion analysis systems and force plates) to small wearable inertial measurement units (IMUs) with embedded gyroscopes, accelerometers, and magnetometers to be used outside the laboratory. For scientific purposes, both laboratory-bound sensors and IMUs are frequently used to determine gait and balance abilities [6,58–60]. However, an assessment device for clinical settings would preferably be small, lightweight, easy to transport and inexpensive. The tri-axial, stand-alone accelerometer, fixed to the trunk at the 3rd lumbar vertebrae, has proven suitable to objectively collect gait data. Additionally, these stand-alone accelerometers have demonstrated reliability and accuracy [61–64]. They have been used for years to quantify gait and offer a large range of movement-describing features. Various time, amplitude, and frequency variables can be computed from trunk acceleration signals in three dimensions. Based on peaks in anterior-posterior (AP) acceleration signals, the foot contacts can be detected [65,66]. From the foot contacts, step and stride variables can be determined, including stride time, stride variability, and step symmetry [67]. Additionally, the root mean squares (RMS) of the acceleration signal provide information about gait variability [67]. Gait smoothness is determined from content signal frequency [68]. Furthermore, gait variables derived from the signal trajectory, such as the sample entropy and maximal Lyapunov exponent, provide insights into the predictability and local stability of gait [69–71].

Numerous studies have demonstrated that data derived from trunk accelerometers can differentiate between gait of young and old healthy adults, fallers and non-fallers, and patient populations and healthy controls [44,50,72]. Old adults seem to walk with less symmetry, more variability, and less stability compared to healthy young adults [73]. Additionally, various gait variables are associated with fall risk, Parkinson’s disease, multiple sclerosis, and dementia [44,47,50,74]. These variables include gait speed, stride time, and different variability and stability-related measures (e.g., local dynamic stability, smoothness, and predictability of gait pattern). Stand-alone accelerometers introduced into clinical practice would facilitate objective and accurate gait assessments to provide a variety of information about gait ability. Despite their advantages over other objective measures, stand-alone accelerometers are still confined primarily to use in the research setting. The need for specialized staff to perform measurements, analyze data, compute variables, and correctly interpret results limits widespread clinical use of stand-alone accelerometers. Clinical practitioners need and want objective devices that measure gait ability easily, accurately, and in a user-friendly way.

*Smart devices as gait assessment instruments*

The recent rapid development of smart phones, iPods, and similar smart devices provides an interesting alternative to assess gait and balance, as they are equipped with build-in, tri-axial accelerometers. Smart devices are relatively cheap, easy to use and many people already possess smart devices. Smart devices have the capacity to collect and store data, which can be conveyed wirelessly to a remote location for data processing. Additionally, data can be sent to other smart devices or a personal computer to provide direct access for clinicians or caregivers without the need for complex software or a patient visit. Applications are being developed to record and store balance and gait task data. These applications might be extended with algorithms that provide feedback to users or clinicians about gait ability.

### *Objectives*

Smart devices seem to have the capacity to accurately and consistently record balance and gait data [75–77]. Nishiguchi et al. (2012) showed that an android-based smartphone can collect reliable and valid gait data in healthy young adults [77]. In addition, Patterson et al. (2014) evaluated software developed to access the iPod and iPhone accelerometer output and translated such data into balance measures. The results of their pilot study indicated that accelerometers provided consistent balance scoring for healthy young adults [75]. However, validity and test–retest reliability might be different for different task conditions or different age groups. Furthermore, a frame of reference for gait changes due to normal aging is still lacking. Therefore, the fourth and fifth objectives of this thesis were to:

4. assess the validity and reliability of the embedded accelerometer in the iPod Touch during gait and postural tasks under different conditions (eyes open, eyes closed, concurrent cognitive dual task) in participants over different ages;
5. determine the relationship between gait variables and age in healthy adults between 18 and 75 years old, and to examine the ability of the gait parameters to discriminate between healthy young and old adults.

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## Outline of this thesis

In the first part of this thesis, the first steps in the realization of a smart fall prevention sensor system to identify long-term care residents with dementia are described. **Chapter 2** provides a synthesis of the effectiveness of fall prevention technologies used in intramural care facilities with respect to fall rate, fall-related injuries, false alarms, and user experience. **Chapter 3** describes the fall rate, fall-related injuries, and circumstances of falls with respect to time, location, and whether or not a fall was witnessed by the staff in a long-term care facility with residents with dementia. Additionally, the relationship between patient characteristics (classified into seven domains: demographics, ADL performance, mobility, cognition and behavior, vision and hearing, medical conditions, and medication use), and fall rate in these long-term care residents with dementia are presented. **Chapter 4** gives an overview of the user requirements of the staff of a long-term care facility for a fall prevention system based on smart technology. This chapter presents what was learned about user experiences with the currently used sensor systems, as well as the specific requirements and expected effects of a new fall prevention system.

The second part of this thesis addresses whether and how the iPod Touch is an appropriate instrument to measure gait ability in young and old healthy adults. **Chapter 5** focuses on the validity and reliability of the embedded accelerometer in an iPod Touch during gait and postural tasks under different conditions in participants over different ages. Young, middle-aged, and old adults performed walking and standing tasks under different conditions (e.g., eyes open, eyes closed, concurrent cognitive dual task) while wearing a stand-alone accelerometer and the iPod Touch. **Chapter 6** pursues a frame of reference for gait changes due to natural aging. Because the inter-relationship between the various gait variables used to characterize gait is unknown, a model is built to investigate the relationship between the gait variables and age. The identified gait variables sensitive to change over age are presented and their ability to distinguish younger adults (ages 18 to 45) from older adults (ages 46 to 75) is described. Finally, the main results of the thesis are summarized, and recommendations and directions for future research and clinical practice are discussed in **Chapter 7**.

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# CHAPTER 2

# Sensor technologies aiming at fall prevention in institutionalized old adults: A synthesis of current knowledge

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## Abstract

### Background

Falls are a serious health problem in old adults especially in nursing home residents and hospitalized patients. To prevent elderly from falling, sensors have been increasingly used in intramural care settings. However, there is no clear overview of the current used technologies and their results in fall prevention.

### Objectives

The present study reviews sensor systems that prevent falls in geriatric patients living in an intramural setting and describe fall rates, fall-related injuries, false alarms, and user experience associated with such systems.

### Methods

We conducted a systematic search for studies that used sensor technologies with the aim to prevent falls in institutionalized geriatric patients.

### Results

A total of 12 studies met the search criteria. Three randomized clinical trials reported no reductions in fall rate but three before-after studies reported significant reductions of 2.4 to 37 falls per 1000 patient days. Although there was up to 77% reduction in fall-related injuries and there was relatively low, 16%, rate of false alarms, the current data are inconsistent whether current sensor technologies are effective in reducing the number of falls in institutionalized geriatric patients.

The occurrence of false alarms (16%) was too high to maintain full attention of the nursing staff. Additionally including the users opinion and demands in developing and introducing sensor systems into intramural care settings seems to be required to make an intervention successful.

### Conclusion

The evidence is inconsistent whether the current sensor systems can prevent falls and fall-related injuries in institutionalized elderly. Further research should focus more comprehensively on user requirements and effective ways using intelligent alarms.

## Introduction

The number of old adults increases at an accelerating rate and falls represent a costly but unsolved safety issue with serious negative consequences for quality of life [1–4]. Compared with the 30% fall rate in community dwelling old adults, the 50% fall rate in elderly living in nursing homes is especially alarming [2,5]. Hospitalized patients fall 2 to 25 times per 1000 patient days [6,7] and one half of the elderly who already fell once will fall again [2]. Twenty percent of those who fell need medical attention for minor (28%) and soft tissue injuries (11%) and for fractures (5%) [2,7]. In addition to the physical trauma, fallers suffer from a loss of self-confidence, anxiety, depression, incomplete rehabilitation, increased length of hospital stay, additional costs for health and social care, and increased morbidity and mortality [2,8,9]. Unsurprisingly, fall prevention has become an important topic.

Fall prevention is an even more of a critical issue in old adults who fall in a nursing home or hospital because these patients are more physically and cognitively impaired than fallers living independently in a community setting [9]. Indeed, patients suffering from confusion and those with a high number of comorbidities are also more prone to falling during hospitalization than their peers living in the community [9]. Further, patients with dementia in a nursing home fall twice as often as elderly with normal cognitive function living also in a nursing home [10]. Over the next years, the number of old adults living in nursing homes will increase and concomitantly it is expected that the absolute number of falls will increase in this population [11]. Therefore, there is an urgent need to improve the efficacy of fall prevention especially in senior patients who reside in intramural care setting. Intramural care settings in this review refer to nursing homes, with geriatric and psychogeriatric departments and hospitals.

Health care workers in intramural care settings (e.g. nurses, nurse assistants, caregivers) often use physical restraints to protect immobile, highly dependent, and cognitively vulnerable elderly against falls [12]. The use of restraints ranges between 41% to 64% of patients in nursing homes and 33% to 68% in hospitals [12]. There is a growing interest in minimizing the use of physical restraint because restraints increase the risk of adverse events such as depression, aggression and confinement, but also due to the greater risk of fall-related injuries, breathing difficulties and even premature death [3,12]. More importantly, there is scant, if any, evidence that physical restraints prevent falls [12]. An alternative and rapidly emerging strategy to fall prevention is the development of light, small and cheap sensor systems [1]. Sensor systems are designed to detect and alert patients and staff about critical events: getting out of bed and rising from a chair unassisted. One common goal guides the rapid evolution of a diverse array of sensor technologies: fall prevention. There are two main classes of sensors available in terms of sensor position: wearable and non-wearable. With respect to detection mechanisms, sensors detect movement by pressure, position and infrared light. Detecting a specific event, such as rising from a chair or moving out of bed, is expected to predict a fall and thus the possibility to prevent the patient from falling.

The inconsistencies in the literature concerning the efficacy of conventional fall prevention methods and the emergence of the new sensor systems warrant a synthesis of the current knowledge concerning fall prevention in institutionalized old adults. Therefore, the aim of the present review is to integrate past and current knowledge concerning fall prevention systems used in intramural care settings. We review the effectiveness of these methods in terms of methodological quality, effectiveness of fall prevention technologies on fall rate and fall-related injuries, false alarms, and user experience. Finally, we make recommendations for future directions of sensor technology development in an effort to improve the efficacy of these systems to detect and prevent falls in institutionalized old adults.

## Methods

### *Search strategy*

A search of the electronic databases Pubmed, Web of Science and Scopus was conducted between September and December 2011, using the search terms: Fall prevention, Reduce falls, Elderly, Technology, Sensor, Monitoring, Telemedicine, Alarms, Ambient Living, Accelerometer and Risk assessment. Articles included were (1) written in English, (2) original research studies, (3) on elderly patients, and (4) the intervention used a sensor to prevent falls in an intramural care setting (e.g. hospital or nursing home). Articles were excluded when a comparison with and without sensor system was impossible. The citation lists of the articles read in full text were checked to complete the article selection.

### *Quality assessment and data abstraction*

The methodological quality was assessed with a modified Downs and Black checklist [13]. The original checklist of Downs and Black consists of 27 items with a maximum score of 32 points [13]. The questions related to follow-ups and adverse events were removed. In addition, the questions about the confounders and power of the study were scored with one instead of the original two and five points. The adapted checklist consists of 23 items with a maximum score of 23 points. We identified four levels of quality: excellent (18 to 23), good (12 to 17), fair (7 to 11), and poor (≤ 6). Two reviewers assessed the quality of the included studies independently.

## Results

### *Article selection*

Figure 2.1 shows the selection process of the final 12 articles from 1020 hits produced by the search. After eliminating 469 items based on title, 470 as duplicates, and 61 abstract-only, 20 articles were qualified for full text reading. Finally, 16 articles were excluded due to the content and 8 articles were added after searching references.

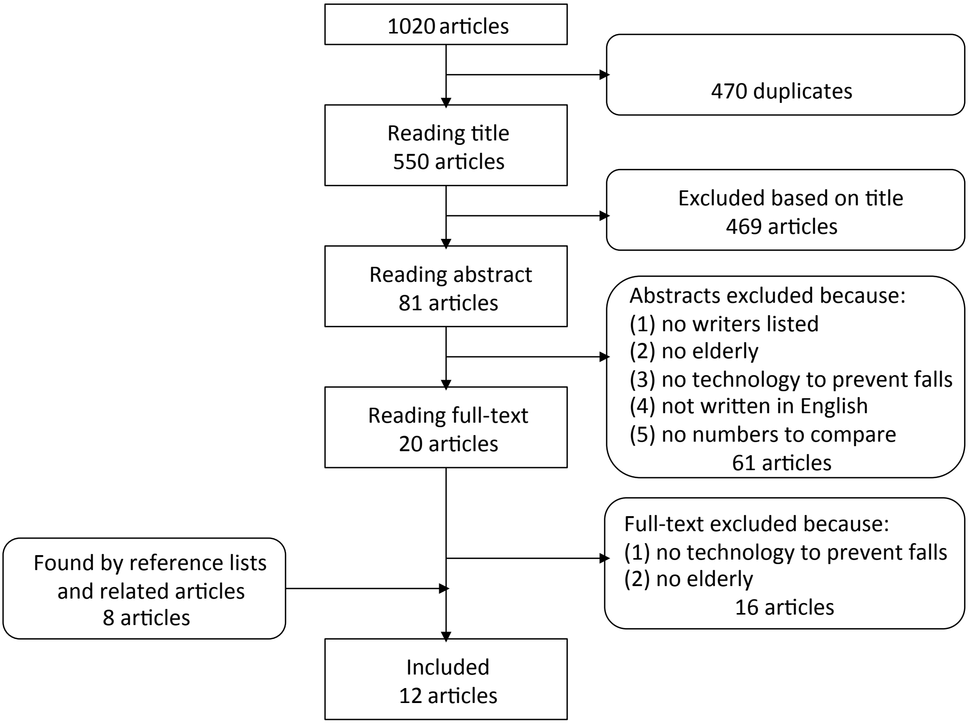


**Figure 2.1** Flow chart of the article selection.

The included articles examined the effects of intervention(s) on fall incident rate, fall-related injuries, user experience, false alarms, physical restraints, and health care costs in the care setting.

### *Methodological quality*

Table 2.1 shows the quality score of the studies ranging from 6 to 19 out of maximum 23 points with a mean (SD) and median of 14.4 (4.1) and 15.5. One article was of poor quality [14], one rated as fair [15], eight achieved good quality [3,16–22], and two were of excellent quality [23,24]. There were three RCT's, eight before-after studies and one control trail included. The scores of the articles were particularly low on the blinding of patients and the outcome assessor (12 of 12), adjustment for confounding factors (8 of 12), and the power to detect whether the outcomes were clinically important (9 of 12). Furthermore, four studies did only report the achieved reduction in falls and did not report the fall rate before and after the intervention or the level of significance.

**Table 2.1** Methodological quality according to the modified Downs and Black checklist. Scores are presented per subscale and the total score per article.

| Article | Reporting | External validity | Internal validity | | Power | Total |
|---|---|---|---|---|---|---|
| | | | Bias | Confounding | | |
| Barker et al. [16] | 6 | 2 | 4 | 1 | 0 | 13 |
| Bressler et al.[4] | 7 | 3 | 4 | 3 | 0 | 17 |
| Cumming et al. [23] | 7 | 3 | 4 | 3 | 1 | 18 |
| Diduszyn et al. [21] | 6 | 2 | 4 | 2 | 1 | 15 |
| Dubner et al. [18] | 6 | 2 | 4 | 2 | 0 | 14 |
| Fonda et al. [19] | 8 | 3 | 4 | 2 | 0 | 17 |
| Kelly et al. [20] | 8 | 2 | 4 | 3 | 0 | 17 |
| Kwok et al. [3] | 6 | 2 | 4 | 3 | 1 | 16 |
| Morton [15] | 4 | 0 | 2 | 1 | 0 | 7 |
| Spetz et al. [22] | 5 | 2 | 4 | 3 | 0 | 14 |
| Tideiksaar et al. [24] | 8 | 3 | 4 | 4 | 0 | 19 |
| Widder et al. [14] | 1 | 1 | 2 | 2 | 0 | 6 |
| **Maximum score** | 8 | 3 | 6 | 5 | 1 | 23 |

### *Fall prevention interventions*

Table 2.2 summarizes the articles included in the review and the characteristics of patients, study settings, interventions and outcomes. The fall prevention sensor systems were mostly used in elderly/psychogeriatric units, acute hospitals and in residential care facilities. Patients with a high risk to fall were selected to use fall prevention sensors, those patients were identified according to their fall history, mental state and mobility level [3,14,15,20,24]. The sensor systems used to prevent falls can be divided into single and multi-factorial interventions using wearable and non-wearable sensors. The studies using a multi-factorial fall prevention program included besides a sensor, data gathering, risk assessment, drug review, an exercise programme, staff and patient education, environmental and equipment changes, and work practice adaptations [15,16,19,23].

*Effectiveness of fall prevention technologies on fall rate and fall related injuries*

The aim of this section is to determine the effect of the fall prevention sensor system on the fall rate and fall related injuries. Figure 2.2 summarizes the effects of sensor interventions on fall statistics after normalizing fall rate per 1000 bed days. Figure 2.3 shows the outcomes for studies in which such normalization was not possible.

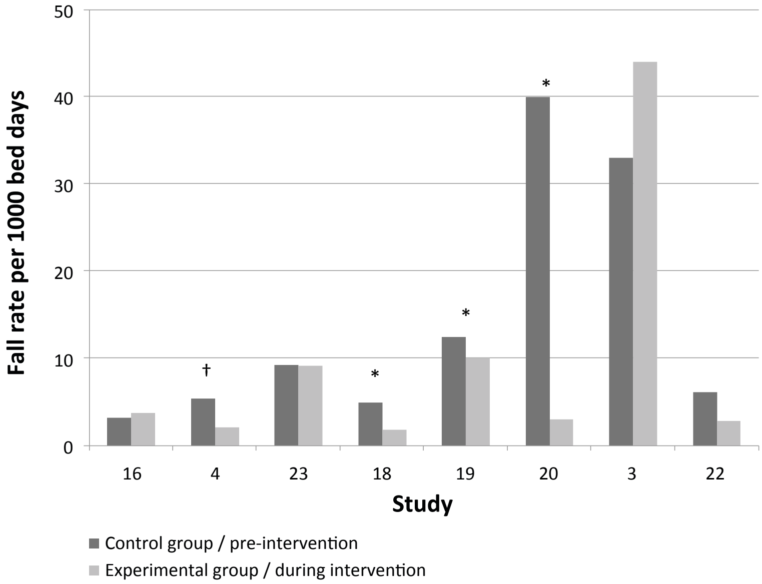


**Figure 2.2** Falls before and during the fall prevention intervention and the falls in the control (no intervention) and experimental group (fall prevention intervention).

* = significant reduction in falls after introducing fall prevention technologies
† = significant reduction in falls after removing fall prevention technologies

*Wearable sensors*

Wearable fall prevention sensors can be attached to a patient's thigh or foot [14,20,23]. Sensors affixed to the thigh have the size and shape of a credit card and are light-weight. These sensors have their own battery power source and are water- and shockproof [14,20]. Nurses and patients are alerted when a patient assumes a weight bearing position [20] or shifts the leg from the horizontal to an angle smaller than 45 degrees [14]. Those alarms seem to be effective in both hospital and nursing home settings in reducing fall rate. However, it appears that the sensors were not feasible for use by those elderly patients who wished to ambulate without imposed limitations and also in confused patients who tried to remove the sensors.

A wearable sensor worn on the foot takes the form of a neoprene rubber sock. The sock contains a pressure switch under the heel and a small loud speaker in a pocket at ankle level [23]. When a patient stands up, the alarm alerts the staff that the patient is standing and requires support [23]. The rubber sock was used in a large, multi-factorial RCT lasting three months and included 3999 patients admitted to 24 acute and rehabilitation wards [23]. Nevertheless, the intervention did not reduce fall rate. The negative result might be

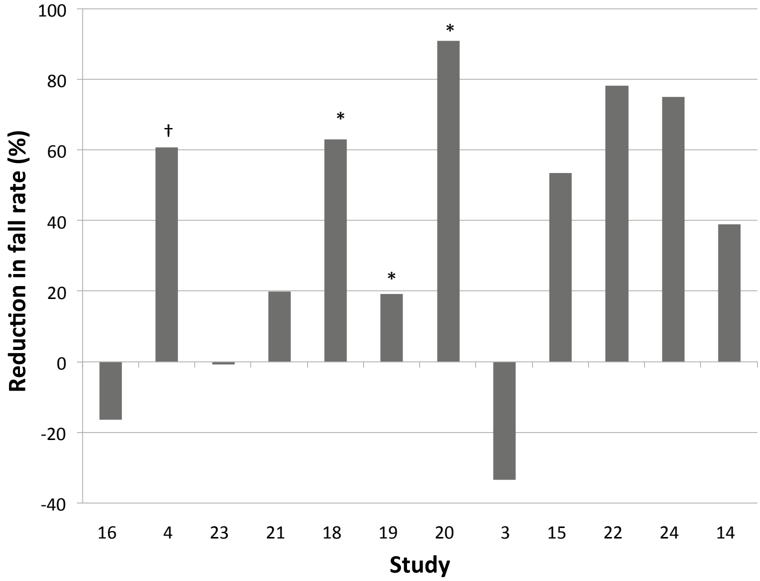


**Figure 2.3** Percentages fall rate reduction.

* = significant reduction in falls after introducing fall prevention technologies
† = significant reduction in falls after removing fall prevention technologies

attributed to the short time the intervention team spent on each ward, preventing the transformation of the current ward culture into a fall prevention environment.

*Non-wearable sensors*

As an alternative to wearable sensors, several non-wearable sensors have been developed to detect the event when elderly patients get out of bed or rise from a chair unassisted. These systems are non-restrictive and operate without cables, cuffs, leads or electrodes [22]. Non-wearable fall prevention sensors are placed in and around beds and chairs.

A frequently used sensor is the pressure-sensitive mat [3,15,21,24]. Pressure-sensitive mats are light-weight plastic sheets [15] placed between the surface of the mattress and the bed sheet [15,21,24]. Some pressure-sensitive mats have a time delay, of about two seconds between detection and sending an alarm, to prevent false alarms [3,15]. The alarms of the sensor mats are triggered when the patient's weight is lifted off the bed and the pressure on the sensor mat is relieved [3,15,21,24]. Two RCT's using the pressure-sensitive mats have failed to observe a reduction in fall rate [3,24], but two before-after studies did find a reduction of 18% and 54% in fall rate [15,21]. The RCT's may have failed to reduce falls because the fall rate was too low (control group n=3, n= 4 and experimental group n= 4, n=1) [3,24]. However, the exact numbers and the level of significance have not been reported in a consistent manner in the before-after studies. It is difficult to determine the effectiveness of the interventions and to compare the results that could suggest which sensor technology and method will be most efficient to use, because of the inconsistent data reporting.

Infrared fall detection systems represent a second category of non-wearable technologies to prevent falls [17,18]. Infrared scanning consists of directional sensors that respond to changes in infrared energy patterns. The infrared beam has an elevation of approximately 90 cm above the floor [18]. The sensors detect a shift in the infrared energy field when a patient sits up in or gets out of bed [18]. In a few cases infrared scanning systems have been successful in reducing falls but only during the night and not during the day [18]. Those sensors can be useful in a small area, however falls are not limited to a bed or chair.

Four of the before-after studies used bed and chair alarms. Unfortunately, these studies failed to characterize in sufficient details the working mechanism of the bed and chair alarms [4,16,19]. Two of these studies were multi-factorial interventions performed in acute care settings, for 3 (n=3961) and 9 years (n=271095). The 3-year during study reduced falls from 12.5 to 10.1 falls per 1000 patient days. The other study did not reduce fall rate, this might be due to the already low fall rate at the start of the intervention, 3.25 falls per 1000 patient days. Additionally, only those two studies investigated the influence of the fall prevention intervention on fall-related injuries [16,19]. The serious fall-related injuries (like; fracture, head injury, permanent disability or death) decreased with 77%, from 0.73 to 0.17 per 1000 bed days [19] and with 64% from 1.48 to 0.72 per 1000 bed days [16]. Unfortunately, it is hard to say which component of the multi-factorial studies reduced fall rate, both studies included bed alarms, toileting protocols, high-low beds and identified patients with a high risk of falling with a sign above their bed [16,19].

The third study used a more advanced system to reduce falls, combining bed sensors with a recording of physiological measurements [22]. A passive sensor array placed under patients' beds measures heart rate and respiration and the bed sensors are incorporated into the sensor array [22]. The heart rate and respiration are determined by a sophisticated algorithm designed to identify potential problems but also eliminating noise in the data to reduce false alarms [22]. If a patient's heart rate and/or respiration rises beyond his/her expected physiological range, a patient is considered to be at risk for a bedside fall, and the system alerts the patient and/or the caregivers [22]. It seems that bedside falls were reduced while using this sensor system. Nevertheless the authors did not report the level of significance, which makes it difficult to draw any firm conclusions.

The fourth study including bed and chair alarms removed the sensor systems systematically from the residential care setting [4]. Due to the false alarms and the dependency of the nurses on the alarms the facility decided to eliminate the bed and chair alarms. After three months phasing out the sensors the fall rate decreased for the next 5 months [4]. The success of this intervention might be distorted by the negative attitude of nurses against the sensor systems and the positive attitude towards the new ward culture without the sensors. Time was spent for education, adaptation and integration of the new

**Table 2.2** Characteristics of the included articles.

| Article | Design | Study characteristics |
|---|---|---|
| Barker et al. (2008) [16] | Before-after design | **Setting:** acute hospital<br>**Population:** 271 095 patients at HFR<br>**Duration**: 9 years (3 years before and 6 years after intervention) |
| Bressler et al. (2011) [4] | Before-after design | **Setting:** 60 bed residential care<br>**Population:** patients with Alzheimer or another form of dementia<br>**Duration**: 11 months |
| Cumming et al. (2008) [23] | Cluster randomised controlled trail<br>Ex & Con | **Setting:** 24 elderly care wards in 12 hospitals<br>**Population:** 3999 patients<br>**Duration:** 3 months |
| Diduszyn et al. (2008) [21] | Before-after design | **Setting:** 3 telemetry floors and 1 neurology floor at a hospital<br>**Population:** patients at HFR<br>**Duration:** 4 months |
| Dubner et al. (1988) [18] | Before-after design | **Setting:** 18-bed PG unit<br>**Population:** PG patients<br>**Duration:** 21 months: no rooms scanned; 17 months: 4 rooms scanned; 15 months: all 9 rooms scanned |
| Fonda et al. (2006) [19] | Before-after design | **Setting:** 4 elderly wards of a hospital<br>**Population:** 3961 patients<br>**Duration:** 3 years |
| Kelly et al. (2002) [20] | Crossover design<br>Pre- during and post measurements | **Setting:** medicare unit of a medical facility<br>**Population:** 47 patients at HFR<br>**Duration:** 5 months |

| Intervention | Outcome measure(s) & Key finding(s) |
|---|---|
| MF programme including bed and chair alarms | **Number of falls**<br>Fall rate increased from 3.25 (2.71, 2.69, 3.63) to 3.75 (3.65, 3.63, 3.63, 3.71, 4.21, 3.55) per 1000 occupied bed days after programme implementation<br>**Number of fall related injuries**<br>rate of fall related injuries reduced sign. from 1.66 (1.55, 1.39, 1.65) to 0.61 (1.31, 0.98, 0.61, 0.65, 0.71, 0.68) per 1000 occupied bed days after programme implementation ($p < 0.001$) |
| Removing bed exit alarms, chair alarms and tabs with clips to the residents | Pre-intervention (with sensors) 5.41 falls per 1000 bed days, intervention (removing sensors) 3.50 falls per 1000 bed days and post intervention (without sensors) 2.12 falls per 100 bed days. Sign. ($p=0.3$) between pre and post intervention period. |
| MF including a neoprene rubber sock<br>**Sensor type:** pressure sensor | **Number of falls**<br>381 falls; no difference in fall rates between Ex & Con (respectively 9.26 and 9.20 falls per 1000 bed days ($p = 0.96$)) |
| The Posey Sitter II wireless Nurse Call Monitor<br>**Sensor type:** pressure sensors | **Number of falls**<br>18% reduction in falls between falls before ($n=78$) and after the intervention ($n=64$). |
| **Sensor type:** Infrared scanning system | **Number of falls**<br>no sign. difference in morning and evening time falls between before installation, during limited use and after installation in all rooms ($F = 1.32$, $p = 0.27$); night time falls decreased sign. after installation in all rooms ($F = 3.62$, $p = 0.034$) |
| MF including a bed alarm | **Number of falls**<br>19% reduction in number of falls from 12.5 falls to 10.1 per 1000 occupied bed days ($p = 0.001$)<br>**Number of fall related injuries**<br>77% reduction in number of falls resulting in serious injuries from 0.73 falls to 0.17 per 1000 occupied bed days ($p < 0.001$)<br>**Staff compliance with the risk assessment**<br>staff compliance increased from 42% to 70% |
| NOC·watch device<br>**Sensor type:** movement sensor | **Number of falls**<br>fall rate decreased sign. from 4.0 to 0.3 to 3.4 falls per 100 patient days ($p = 0.02$)<br>**Effects on skin integrity**<br>no adverse effects on skin integrity<br>**Staff and patient acceptance**<br>high staff acceptance of the device, 6 patients tried to remove the device<br>**False alarms**<br>two false alarms |

**Table 2.2** Continued.

| Article | Design | Study characteristics |
|---|---|---|
| Kwok et al. (2005) [3] | Randomized controlled trail | **Setting:** two 27-bed geriatric stroke rehabilitation wards of a hospital<br>**Population:** 180 geriatric patients at HFR<br>**Duration:** 10 months |
| Morton (1989) [15] | Experimental design | **Setting:** 42-bed medical unit of medical centre<br>**Population:** patients at HFR<br>**Duration:** 5 years (2 years with the alarm system) |
| Spetz et al. (2007) [22] | Trial<br>Ex & Con | **Setting:** 24-bed post-neurosurgery unit of a hospital<br>**Population:** in-patients<br>**Duration:** 8 weeks |
| Tideiksaar et al. (1993) [24] | Randomized controlled trail | **Setting:** 16-bed acute-care facility of a medical centre<br>**Population:** 70 patients at HFR<br>**Duration:** 9 months |
| Widder et al. (1985) [14] | (1) Pilot study<br>(2) Complete in use<br>Before-after design | **Setting:** (1) 16 patients, (2) all patients, of the orthopaedic and general medicine unit of a hospital<br>**Population:** patients at HFR<br>**Duration:** (1) 1 month;<br>(2) 5 months |

HFR = high fall risk; sign. = significant(ly); Ex & Con = Experimental group (intervention) and Control group (no intervention); MF=Multi-Factorial intervention; PG = psycho-geriatric; ADL= activities of daily living

working method [4]. However, the study failed to report if indeed there were changes in the education, adaptation and integration system before and during the introduction of the sensor systems. Maybe more time and a good education program about the use of bed and chair alarms would have had a positive effect on fall-rates.

*Feedback*

Fall prevention sensor systems give feedback to patients and nurses when an alarm is triggered. There are a variety of alerts possible. Alarms can go to the nurses' station and beepers in the form of audio and visual alarms [3,15,21,24]. Bedside alarms warn

| Intervention | Outcome measure(s) & Key finding(s) |
|---|---|
| Bed and chair sensors<br>**Sensor type:** pressure sensitive bed mat<br>**Time delay:** 2 seconds | **Physical restraints use**<br>no sign. differences in physical restraint use<br>**Mobility and transfer ability**<br>no improvements in mobility and transfer ability<br>**Number of falls**<br>no improvement in fall rate between Ex (n=4) & Con (n=3) |
| MF, after 2 years a bedcheck alarm was added<br>**Sensor type:** pressure sensitive bed mat | **Number of falls**<br>one year after adding the Bedcheck alarm falls reduced with 47%, and after another year with 60%<br>**Number of recurrent falls**<br>the percentage of recurrent falls dropped with 29 % in two years |
| LG1 Intelligent Medical Vigilance® system<br>**Sensor type:** passive sensor array with bed-exit sensors | **Cost-effectiveness**<br>cost saving compared to patient sitters<br>**Number of falls**<br>fall rate decreased between Ex (n=2) and Con (n=15) |
| The RN+ OnCall bed monitoring system<br>**Sensor type:** pressure sensitive bed mat | **Number of falls**<br>no sign. difference in bed falls between Ex (n=1) & Con (n=4) (p=1.00)<br>**Performance of bed alarm system**<br>system functioned properly<br>**Staff and patient acceptance**<br>well accepted by patients, families and nurses |
| Ambularm<br>**Sensor type:** movement sensor | **Number of falls**<br>(1) no falls<br>(2) general medicine unit reduced falls with 45%; orthopedic unit reduced falls with 33%<br>**Patients acceptance**<br>A few confused patients tried to remove the Ambularm |

the patients that they have to sit or lay down again. A previously recorded message (e.g. "please stay in bed") [24] tells the patients what to do, or an audio (bleeping sound) or visual signal (flashing light) alerts the patient [3]. Bedside call buttons and dim lights can be activated [17,18] and there are systems with flexible settings, allowing caregivers to customize alerts (tones, voice recording, lights, and other messaging methods) [22]. Nursing home residents can respond negatively to an audio alarm; become agitated or attempt to move away from the unpleasant sound [17]. On the other hand, cognitively impaired patients were sitting down again as a response to the sound of the alarm [20]. It depends on the individual patients which kind of feedback is appropriate and successful.

False alarms

Bressler et al (2011) removed bed and chair alarms because false alarms desensitized the support staff [4]. False alarm reporting is still scarce in the current literature as only one study presented the numbers of alarms and false alarms. Tideiksaar et al. (1993) used sensitive pressure mats to prevent falls in an acute care setting [24]. There were 143 alarms noticed during 4425 hours of sensor use, 16% of those being false alarms [24]. Another study with a wearable sensor worn on the thigh reported two false alarms and a study with a pressure sensitive mat reported a low number of false alarms without specifying the exact numbers [20,21]. A part of the false alarms were the consequence of mats lying under the patient shoulders instead of under the buttocks [24]. Restlessness in patients resulted in frequently false alarms and a part of the false alarms could not be explained [24]. It is important to have a sensor system with a low number of false alarms to maintain full attention of the health care workers.

*User experiences*

User acceptance influences the effectiveness of an intervention. When health care workers do not see the need of using sensor systems or there is no time to get used to a device the sensor systems won't be used correctly or won't be used at all. The few studies investigating staff acceptance reported that health care workers accepted the fall prevention sensors well in their care setting [19,20,24]. Health care workers asked to add patients with a high risk of falling to the intervention group [20], and caregivers preferred sensor systems above mechanical restraints [24]. However, studies who introduced a sensor system without success, reported the lack of acceptance and awareness of the fall prevention sensor system as a limitation in their study [21,23]. Inexperience with the use of the sensor system and the amount of time required to program and install the sensor systems are barriers for health care workers to use sensor systems [21]. Bressler et al (2011) removed the sensors from the residential care institution because the health care workers relied too much on the sensors and the level of care has decreased [4]. Working without sensors was slowly introduced in combination with education. The management team modified the environment, leading to a new culture associated with sensor use [4]. It seems that the staff accepted the changes, leading to a large degree to the success of the intervention.

## Discussion

The aim was to review the effects of fall prevention sensor technologies in patients residing in intramural care facilities. We addressed four specific issues: 1) fall and 2) fall-related injury rates in the presence of sensor systems, 3) the number of false alarms, and 4) the experiences of health care workers and patients with fall prevention sensor systems.

There is no consistent evidence that the implementation of current sensor technologies in intramural care settings would reduce fall rates. Wearable sensors attached to the thigh and a non-wearable infrared sensor seem to reduce falls, however the wearable sensors are not feasible for confused patients and the infrared sensor is only effective at night. There is no consensus concerning efficacy of pressure-sensitive sensors and bed-exit alarms to reduce fall rates, the reported outcomes were possibly related to the poor quality of the sensors. The simplest sensors monitor only one variable (e.g., standing up) in a small area (e.g., around the bed or chair) but it is well-established that falls occur in a variety of conditions characterized by a wide array of spatial and temporal distribution. Hospital and nursing home patients fall not only when they get out of bed or rise from a chair. Falls also occur as a result of trips and slips in bathrooms, hallways, and living rooms, 24 h a day [1,25]. The results of the present review suggest that sensor systems monitoring a small area and a single variable are not appropriate to prevent falls in nursing home residents or in hospitalized elderly.

Sensors may not prevent the total number of falls per se but could reduce the severity injuries caused by falls. Multi-factorial studies using a sensor system in combination with other fall prevention methods revealed a reduction in fall-related injuries. Unfortunately, a consistent problem with multi-factorial interventions is that it is not clear which component of the intervention causes reductions in fall-related injuries [16,19] and fall rates [19]. It is possible that not the sensor itself but other elements of the multi-factorial fall prevention program or the interaction between the sensor and elements of the multifactorial intervention might cause the reduction in fall-related injuries. There is a need to conduct carefully designed studies that examine the independent and the potentially interactive effects between sensor system and other elements of the intervention.

More research is also needed towards the number of false alarms. A high number of false alarms can desensitize caregivers against alarms [26]. To maintain caregivers' responsiveness, 90% of the alarms must be accurate [27]. However, there is only one study that reported the rate of false alarms, 16% [24], a rate we consider still too high. A time threshold can reduce the number of false alarms so that the alarm is triggered after a certain period of time [26]. A time threshold relative to the event will decrease false alarms but is unclear if it would decrease fall risk. Actually, to prevent falls health care workers have to be with the patient before the patient stands up or gets out of bed. In reality, an early warning system is needed that predicts fall risk in a nursing home setting that would allow care givers to act in time to prevent a fall [26].

Reducing false alarms will change the attitude of health care workers towards a sensor system. Attitude towards and integration of fall prevention sensor systems into daily care is a major determinant whether an intervention succeeds or not [4,19,20,25]. Currently the acceptance of fall prevention sensor systems is not universal, with a few studies reporting positive [19,20,24] and other studies reporting somewhat mixed results in terms of incorporating sensor systems in care [3,23]. These latter studies highlight the difficulty of integrating fall prevention sensor systems into the clinical environment because designers and technicians very often approach the problem from a technical and not from a user perspective. The data from this review suggest that health care providers and sensor manufacturers must work together more closely in an effort to develop a dependable, accurate, and user-friendly sensor system [26]. Besides the user-involvement during the development and introduction of the sensor system there is time needed to introduce and integrate the system into the care setting. Optimal conditions have to be created to implement a sensor system.

Health care workers are not the only users of sensor systems, but patients are also involved. The severity of patients' medical condition further complicates user experience with sensor systems and affects effectiveness of interventions. Alternative options to wearable sensors are needed for patients who are unable to cope with the inconveniences and physical limitations presented by the sensors, suffer from confusion or simply remove the sensors [14,20]. One option is the installation of non-wearable sensors that altogether eliminate contact between sensors and patients. However, dementia patients in nursing homes often suffer from restlessness a condition that is associated with a high rate of false alarms [28]. Taken together, the data suggest that there is an urgent need to integrate the process of designing and manufacturing wearable and non-wearable sensor technologies for individual patient and health care staff needs.

Besides the individual demands for the physical qualities of a sensor system it is important to know which patient has a high risk to fall. Although there are numerous instruments for fall risk assessment there is no consensus about a tool or protocol that predicts a fall. If there are criteria for the use of a fall prevention sensor system it is often based on a single fall risk factor or on the opinion of the health care worker [21]. However, falling is a complex phenomenon and a multivariate approach is needed to find patients who require fall prevention systems. Fall risk factors and underlying mechanisms need to be monitored with an intelligent system. Intelligent systems use algorithms to interpret raw data and provide predictive models [26]. The challenge is to make a model and alarm system working for all patients, even for patients who differ from the general patient population. An intelligent alarm system predicting falls for individual patient is the next step in fall prevention to improve accuracy and efficacy.

### *Limitations*

Two factors, the relatively low methodological quality of the included studies and the low number of the studies qualifying for inclusion, limit the conclusions and recommendations the current review can offer. We noticed especially substantial methodological deficiencies concerning the subscales ‘internal validity – confounding’ and statistical ‘power’ and the subscale ‘reporting’ with the subscale ‘internal validity – bias’ suggested somewhat higher qualities. Additional methodological weaknesses included unreported significance level, sample size, and number of (false) alarms. Many additional critical details were lacking in articles published before 1990 [14,15,18]. Such methodological issues make it difficult to compare the outcomes across studies and make recommendations for improving the effectiveness of intervention. Further research about fall prevention systems should include randomised control trials with sufficient power to improve the methodological quality and make the results generalizable.

Besides the methodological issues our review focuses only on sensor technology used in intramural care settings. Hospitalized elderly and old adults living in nursing homes have more risk to fall than old adults living in the community [2,4]. Additionally, the organisation, patient population, care (nurses, caregivers) and consequently the implementation of sensor technology in intramural care facilities differ largely from that of smart home technologies for independent living elderly and/or patient groups [29,30]. There is however, a wide field of sensor technologies used in health care (e.g., ambient intelligence, smart homes and e-health services) to support and monitor older adults with and without cognitive impairments living in the community [31,32] which are not discussed in the present review. Further research should be done to get an overview of the used fall prevention systems in home based situations and the effectiveness of those sensor systems.

## Conclusion and recommendations

Currently there is still an absence of high-quality, multi-centre randomized trials using wearable or non-wearable fall detection and prevention sensor systems, implicitly suggesting that the overall quality of the reviewed studies is average at best. Clinical applications of these sensor systems have not been defined yet in an evidence-based manner. New technologies will provide new options to improve the clinical application of sensor systems. However, additional studies that will address the following issues are indicated:

- To develop sensor systems which cover rooms and units for 24 hours a day. Sensor system should be applicable in a large variety of circumstances and not only around the bed or a chair.
- To map the individual risk of falls and the underlying processes which will provide an algorithm predicting falls.
- To include the users opinion and demands in developing and introducing sensor systems into intramural care settings. Time and space is needed to practice and get used to the sensor system and to use it correctly.

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# CHAPTER 3

# Factors related to the high fall rate in long-term care residents with dementia

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## Abstract

**Background**
Falls in long-term care residents with dementia represent a costly but unresolved safety issue. The aim of the present study was to (1) determine the incidence of falls, fall-related injuries and fall circumstances, and (2) identify the relationship between patient characteristics and fall rate in long-term care residents with dementia.

**Methods**
Twenty long-term care residents with dementia (80±11 years; 60% male) participated. Falls were recorded on a standardized form, concerning fall injuries, time and place of the fall incident and if the fall was witnessed. Patient characteristics (66 variables) were extracted from medical records and classified into the domains: demographics, activities of daily living, mobility, cognition and behavior, vision and hearing, medical conditions and medication use. We used partial least squares regression to determine the relationship between patient characteristics and fall rate.

**Results**
A total of 115 falls (5.1±6.7 falls/person/year) occurred over 19 months, with 85% of the residents experiencing a fall, 29% of the falls had serious consequences and 28% was witnessed. A combination of impaired mobility, indicators of disinhibited behavior, diabetes, and use of analgesics, beta blockers and psycholeptics were associated with a high fall rate. In contrast, immobility, heart failure, and the inability to communicate were associated with lower fall rates.

**Conclusion**
Falls are frequent and mostly unwitnessed events in long-term care residents with dementia, highlighting the need for more effective and individualized fall prevention. Our analytical approach determined the relationship between a high fall rate and cognitive impairment, related to disinhibited behavior, in combination with mobility disability and fall-risk-increasing-drugs.

## Introduction

Falls in long-term care residents with dementia represent a costly but unsolved safety issue with serious negative consequences for the quality of life. Sixty percent of the nursing home residents fall at least once a year [1]. These falls often result in injuries, a loss of independence, and early death [2]. Old adults with dementia have two to three times higher fall rates than old adults without cognitive impairments [3] and have lower recovery rates after an injurious fall [4]. Over the past decade, fall prevention in long-term care residents with dementia has become an important topic.

Despite a recent surge in the number of fall prevention intervention studies, there is a lack of successful fall prevention programs for long-term care residents with dementia [5,6]. The development of an effective fall prevention program requires information concerning factors that induce falls [4,7]. Complex interactions among these factors underlie the many falls in old adults [8]. Factors contributing to falls in old adults include age, male sex, incontinence, psychoactive medication use, previous falls, mobility assistance, wandering and a loss of balance [3,9–12]. However, long-term care residents with dementia have additional risk factors compared with those present in community-dwelling old adults [13] and the combination of simultaneously present co-morbidities, cognitive impairments, and frailty substantially increases the fall risk [14]. It is therefore a research priority to identify specific factors and their interactions to reduce fall rate among long-term care residents with dementia. If this effort is successful then the next step would be the development of personalized and effective fall prevention programs [7,15]. Therefore, the objectives of the present study were to:

(1) determine fall rate, fall-related injuries and circumstances of these falls in terms of time, location and whether or not a fall was witnessed by the staff; and
(2) examine the relationship between patient characteristics, classified into seven domains (demographics, ADL performance, mobility, cognition and behavior, vision and hearing, medical conditions and medication-use), and fall rate in long-term care residents with dementia.

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## Methods

### *Participants*

This study was conducted in a Dutch nursing home providing long-term residential (in-patient) care. The research population consisted of residents living on a 20-bed closed psychogeriatric ward between September 2011 and April 2013. All residents had a diagnosis of dementia and were unable to live independently. The psychogeriatric ward had seven single and seven double bedrooms, with showers and lavatories in the hallway. Most residents spent their day in a shared living room.

The Ethical Committee of the Center of Human Movement Sciences at the University Medical Center Groningen approved the research proposal. Because participants were unable to sign the informed consent, we obtained consent from the legal representative of each resident.

### *Data collection*

The data collection was prospective and naturalistic; patient characteristics and falls were observed and recorded during a 19-months long period. Information about patient characteristics already available in the long-term care facility was analyzed with respect to fall rate. For the purpose of the present study, we performed no additional measurements.

*Fall characteristics*

The staff recorded all witnessed and unwitnessed falls on a structured fall incident form. An event was considered as a fall when the staff saw a patient landing on the floor or a patient was found lying on the floor as a result of a fall. The fall incident form allowed the staff to record the precise time and location of a fall, whether the fall was witnessed or not, and the consequences of the fall (e.g., bruises, injuries). To optimize data collection, we reviewed patients' charts once a week. Of all falls, 15 falls were only recorded in the patient charts and not registered on the fall incident form. Fall rate was expressed as the mean number of falls per year per resident.

*Patient characteristics*

Patient characteristics were extracted from the electronic medical records consisting of standard nursing home charts and structured questionnaires. Medical records had the following categories of information: demographics, activities of daily living (ADL), mobility, cognition and behavior, vision and hearing, and medical conditions. Furthermore, the resident's on-going medication-use was extracted from the pharmacist's drug records and categorized according to the Anatomical Therapeutic Chemical (ATC) classification system [16]. Table 3.1 summarizes the patient characteristics. Due to the representation of the information in the nursing home charts and the proposed statistical analyses, the characteristics were binary coded as being present or not.

### *Data analyses*

We report mean, standard deviation, percentage, range and frequency with respect to fall rate, circumstances of falls, and patient characteristics.

To determine the relationship between 66 patient characteristics and fall rate, a multivariate Partial Least Squares (PLS) regression analysis was performed. Fall rate was predicted from the set patient characteristics. This prediction was achieved by the identification of underlying latent factors, which best modelled fall rate, thereby explaining as much as possible of the covariance between patient characteristics and fall rate [17–19].

To have equal importance of the variables, the binary coded patient characteristics (Table 3.1) were pre-processed by setting means to zero. Fall rate, a continuous variable, was positively skewed, and was therefore log-transformed to obtain a normal distribution. Thereafter, the means were set to zero and standard deviations to one.

The PLS model was evaluated by cross-validation (method: Venetian blind; number of data splits: 4). The optimal number of latent factors was determined by stop adding latent factors as soon as the Predicted Residual Sum of Squares (PRESS) decreased. The following output parameters were generated to evaluate the model quality and to quantify the relationship between patient characteristics and fall rate: $R^2$, variance captured in patient characteristics, weight and score plots, the variable importance on projection (VIP) and regression coefficients.

$R^2$ denotes the goodness of fit of the model. The amount of variance in patient characteristics captured by the models latent factors provides an indication of the relevance of the characteristics in the prediction of fall rate. A characteristic is considered completely relevant if its modeling power is 100%, characteristics with a modeling power around 4.5% (latent factor/number of patient characteristics) are of little relevance. Score and weight plots illustrate the relationship between observations (the included patients) and patient characteristics, respectively, with respect to the latent factors. To determine the importance of each characteristic of interest in the final model, the variable importance in projection (VIP) and the variables regression coefficient were calculated. The VIP summarizes the importance of patient characteristics in the PLS model; a VIP Score > 1 is considered important. The regression coefficient is a measure of the association between each patient characteristic and fall rate; a higher value indicates a stronger association.

The PLS analyses was performed using the PLS_toolbox for MATLAB (version 3.7.1; Eigenvector Research Inc., Wenatchee, WA, USA).

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## Results

### *Patient and fall characteristics*

During the study period, a total of 23 patients resided in the closed psychogeriatric ward. Three residents were excluded due to incomplete data, leaving data from 20 patients for analysis (mean age 79.5 years; range 55-95). Table 3.1 shows the patient characteristics.

A total of 115 falls (mean 5.1 ± 6.7 falls/person/year) occurred during the study period. The staff witnessed 28% of falls. Seventeen residents (85%) experienced one or more falls during the study period: three residents did not fall, three fell once, and 14 residents fell more than once. Falls most frequently occurred in the bedroom (39%) and common living room (31%). Falls occurred independently of the time of day, most at 11 am (15%). Twenty-nine percent of the falls resulted in an injury (e.g., bruises, fractures). Two patients suffered a hip fracture and died within a month from complications. Table 3.2 gives an overview of location, time and consequences of falls.

**Table 3.1** Prevalence of the patient characteristics in the research population (n=20) is presented in the left column. The variance captured by each latent factor (LF) for the characteristics is presented in the right columns. The explained variance in patient characteristics (X) and fall rate (Y) per latent factor is presented in the last rows.

| Patient characteristics | | Prevalence | | Variance Captured (%) | | | |
|---|---|---|---|---|---|---|---|
| | **Description** | **n** | **(%)** | **LF 1** | **LF 2** | **LF 3** | **Total** |
| *Demographics* | | | | | | | |
| Female | | 8 | (40%) | 2.24 | 0.41 | 19.58 | 22.22 |
| ≥ 80 years | | 10 | (50%) | 3.56 | 2.16 | 3.55 | 9.27 |
| *Activities of Daily Living(ADL)* | | | | | | | |
| Eat & Drink | Unable to eat and drink independently | 14 | (70%) | 20.17 | 17.73 | 12.49 | 50.39 |
| Poor intake | Malabsorption and poor moisture intake | 4 | (20%) | 3.73 | 2.31 | 0.74 | 6.78 |
| Incontinent | Does not have the ability to control urine and faces | 12 | (60%) | 39.27 | 33.69 | 1.03 | 73.99 |
| Day & night | Unable to control day and night rhythm independently | 10 | (50%) | 29.63 | 4.96 | 3.28 | 37.87 |
| (un)dressing | Unable to (un)dress independently | 16 | (80%) | 43.03 | 2.34 | 4.20 | 49.56 |
| Activities | Unable to control daily and recreation activities independently | 18 | (90%) | 30.92 | 2.24 | 4.76 | 37.92 |
| *Mobility abilities* | | | | | | | |
| Incorrect posture | Unable to take the correct posture to a particular activity | 7 | (35%) | 48.17 | 14.22 | 15.60 | 77.99 |
| Immobility | Physically incapable of independent propel | 8 | (40%) | 33.81 | 2.65 | 0.26 | 36.72 |
| Walking difficulties | e.g., taking small steps, walking bended, shuffle | 13 | (65%) | 28.99 | 0.58 | 12.02 | 41.59 |
| Walking aid | | 6 | (30%) | 0.87 | 1.67 | 2.61 | 5.15 |
| Wheelchair | | 5 | (25%) | 1.94 | 24.38 | 11.14 | 37.46 |
| Transfer problems | Problems with transfer chair | 9 | (45%) | 6.83 | 32.26 | 11.11 | 50.19 |
| Balance problems | e.g., unsteady walking, seeks support during walking | 7 | (35%) | 37.77 | 0.10 | 7.14 | 45.00 |
| Foot problems | Feet inconveniences/wearing unsafe footwear | 15 | (75%) | 1.52 | 42.26 | 0.63 | 44.41 |
| Fatigable | | 14 | (70%) | 16.05 | 0.21 | 10.75 | 27.01 |
| Slow reaction time | Slow reaction time during movements | 11 | (55%) | 1.36 | 6.41 | 14.68 | 22.45 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Cognition and behavior* | | | | | | | |
| Poor communication | Unable to communicate | 10 | (50%) | 38.88 | 38.45 | 0.53 | 77.87 |
| Not aware of values | Not aware of the generally accepted rules and the beliefs about what is desirable behavior | 16 | (80%) | 19.04 | 6.86 | 14.85 | 40.75 |
| Takes risks | Takes too many risks in activities and in contact with others causing unsafe situations for the resident and/or others (e.g., unadjusted walking speed to situations that require adjustments, disrupting personal space of others | 9 | (45%) | 41.19 | 0.69 | 14.75 | 56.63 |
| Physically aggressive | Behavior causing or threatening physical harm towards oneself or others. e.g., hitting, kicking, biting | 4 | (20%) | 33.49 | 0.55 | 3.65 | 37.68 |
| Physically nonaggressive | Inappropriate motor activity that does not involve physical harm. e.g., restlessness, uncooperativeness, wandering, hiding objects | 4 | (20%) | 26.33 | 12.14 | 10.17 | 48.64 |
| Verbally aggressive | Harmful behavior that is both unprovoked and repeated. e.g., yelling, screaming, swearing and name calling | 6 | (30%) | 1.48 | 0.00 | 18.83 | 20.31 |
| Verbally nonaggressive | Inappropriate vocal activity, e.g., repeating sentences | 4 | (20%) | 28.47 | 7.90 | 0.14 | 36.51 |
| Anxious | Is frequently anxious, restless or emotional | 6 | (45%) | 4.17 | 3.45 | 14.20 | 21.83 |
| Confused | Is frequently confused or has hallucinations | 9 | (30%) | 0.07 | 0.46 | 5.45 | 5.98 |
| Urge to move | Has the urge to move | 4 | (20%) | 16.97 | 1.35 | 8.08 | 26.40 |
| Aphasia | Unable to verbally express | 6 | (30%) | 14.39 | 32.59 | 0.02 | 47.00 |
| Agnosia/apraxia | Disturbances in perception and assessment | 8 | (40%) | 4.78 | 22.74 | 4.52 | 32.04 |
| *Vision and hearing* | | | | | | | |
| Visual problems | | 9 | (45%) | 7.50 | 5.96 | 25.65 | 39.11 |
| Hearing problems | | 3 | (15%) | 1.40 | 0.69 | 6.58 | 8.67 |
| *Medical conditions* | | | | | | | |
| Dementia NS | Dementia syndrome Not Specified | 9 | (45%) | 19.08 | 1.94 | 0.04 | 21.05 |
| Lewy Body | | 1 | (5%) | 0.69 | 7.42 | 1.69 | 9.81 |
| Alzheimer | Alzheimer's disease | 5 | (25%) | 0.10 | 0.00 | 0.09 | 0.20 |

**Table 3.1** Continued.

| Patient characteristics | | Prevalence | | Variance Captured (%) | | | |
|---|---|---|---|---|---|---|---|
| | **Description** | **n** | **(%)** | **LF 1** | **LF 2** | **LF 3** | **Total** |
| Vascular dementia | | 2 | (10%) | 2.14 | 5.59 | 31.93 | 39.66 |
| Frontal lobe | Frontal lobe dementia | 3 | (15%) | 41.18 | 2.75 | 10.91 | 54.85 |
| Diabetes | | 7 | (35%) | 4.87 | 14.31 | 3.47 | 22.64 |
| Parkinson | Parkinson's disease | 2 | (10%) | 1.42 | 1.33 | 3.89 | 6.64 |
| Heart failure | | 8 | (40%) | 39.74 | 4.54 | 4.03 | 48.31 |
| Depression | | 5 | (25%) | 0.67 | 1.86 | 0.93 | 3.46 |
| Edema | | 5 | (25%) | 0.20 | 16.03 | 22.29 | 38.52 |
| Respiratory problems | | 2 | (10%) | 0.07 | 3.97 | 8.73 | 12.77 |
| *Medication use* | | | | | | | |
| Polypharmacy | Medication use ≥ 4 | 19 | (95%) | 0.17 | 16.06 | 0.09 | 16.31 |
| A01 | Stomatological preparations | 2 | (10%) | 13.01 | 0.78 | 3.57 | 17.36 |
| A02 | Drugs for acid related disorders | 8 | (40%) | 7.31 | 4.21 | 4.01 | 15.53 |
| A06 | Drugs for constipation | 13 | (65%) | 1.00 | 0.81 | 10.06 | 11.87 |
| A07 | Antidiarrheal, intestinal anti-inflammatory/anti-infective agents | 1 | (5%) | 0.11 | 1.58 | 0.29 | 1.97 |
| A10 | Drugs used in diabetes | 7 | (35%) | 4.87 | 14.31 | 3.47 | 22.64 |
| A11 & A12 | Vitamins & mineral supplements | 19 | (95%) | 1.05 | 0.00 | 0.00 | 1.06 |
| B01 | Antithrombotic agents | 11 | (55%) | 12.32 | 0.03 | 0.01 | 12.36 |
| B03 | Antianemic preparations | 3 | (15%) | 28.43 | 0.62 | 0.24 | 29.28 |
| C01 | Cardiac therapy | 3 | (15%) | 5.14 | 4.43 | 8.45 | 18.02 |
| C03 | Diuretics | 7 | (35%) | 0.00 | 0.26 | 4.15 | 4.41 |
| C07 | Beta blocking agents | 4 | (20%) | 0.34 | 14.10 | 6.13 | 20.57 |
| C09 | Agents acting on the renin-angiotensin system | 5 | (25%) | 2.43 | 9.38 | 23.61 | 35.41 |
| C10 | Lipid modifying agents | 2 | (10%) | 3.74 | 0.00 | 0.01 | 3.75 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| D | Dermatologicals | 4 | (20%) | 0.19 | 0.47 | 1.61 | 2.27 |
| H | Systemic hormonal preparations, excl. sex hormones and insulins | 2 | (10%) | 0.97 | 0.78 | 0.19 | 1.93 |
| N02 | Analgesics | 7 | (35%) | 26.82 | 10.17 | 1.58 | 38.58 |
| N03 | Antiepileptics | 5 | (25%) | 1.20 | 1.40 | 7.17 | 9.77 |
| N04 | Anti-Parkinson drugs | 2 | (10%) | 1.42 | 1.33 | 3.89 | 6.64 |
| N05 | Psycholeptics | 9 | (45%) | 25.90 | 0.05 | 2.67 | 28.61 |
| N06 | Psychoanaleptics | 10 | (50%) | 2.57 | 0.30 | 5.54 | 8.42 |
| R | Respiratory system | 1 | (5%) | 1.86 | 8.07 | 0.02 | 9.95 |
| S | Sensory organs | 3 | (15%) | 17.56 | 5.03 | 3.27 | 25.87 |
| | | | Explained X-variance (%) | 14.05 | 8.01 | 7.06 | 29.58 |
| | | | Explained Y-variance (%) | 62.32 | 27.19 | 6.84 | 96.35 |

**Table 3.2** Fall characteristics.

| | | | |
|---|---|---|---|
| *Number of falls (n=115)* | | | |
| Mean number of falls/person (SD) | 5.8 | (7.3) | Range 0-31 |
| Mean days on ward/person (SD) | 532.4 | (128.5) | Range 145-578 |
| Mean fall rate, falls/person/year (SD) | 5.1 | (6.7) | Range 0-25 |
| *Location of the fall (n=114)* | | | |
| Corridor | 19 | (17%) | |
| Living room | 35 | (31%) | |
| Bedroom | 45 | (39%) | |
| Bathroom/Toilet | 7 | (6%) | |
| Garden | 6 | (5%) | |
| Nurse station | 2 | (1%) | |
| *Fall during time of the day (n=112)* | | | |
| Midnight to 3:59 am | 14 | (13%) | |
| 4:00 am to 7:59 am | 12 | (11%) | |
| 8:00 am to 11:59 am | 34 | (31%) | |
| Noon to 3:59 pm | 17 | (16%) | |
| 4:00 pm to 7:59 am | 18 | (16%) | |
| 8:00 pm to 11:59 pm | 17 | (16%) | |
| *Fall consequences (n=114)* | | | |
| Pain | 15 | (13%) | |
| Bruising or swelling | 10 | (9%) | |
| Wound or graze | 19 | (17%) | |
| Fracture | 4 | (4%) | |
| Witnessed falls | 32 | (28%) | |

### *Fall-related factors*

PLS-regression analysis was used to determine the relationship between 66 patient characteristics and fall rate. The optimal model contained three latent factors, explaining 96% of the overall variance in fall rate, with a fit of 0.92 ($R^2$). The first latent factor explained 62.3% of the variance in fall rate, the second 27.2% and the third 6.8% of the data's variance. In addition to patients' characteristics, Table 3.1 also shows the variance captured in each patient characteristic by the three latent factors of the model. Patient characteristics most relevant to the first latent variable were: incorrect posture (48%), unable to (un)dress independently (43%), taking risks (41%), having frontal lobe dementia (41%), presence of heart failure (40%), incontinence (39%) poor communication (39%) and having balance problems (38%). By the second latent factor most variance was captured in foot problems (42%) and poor communication (38%). The third factor captured most variance in the presence of vascular dementia (32%) and visual problems (26%).

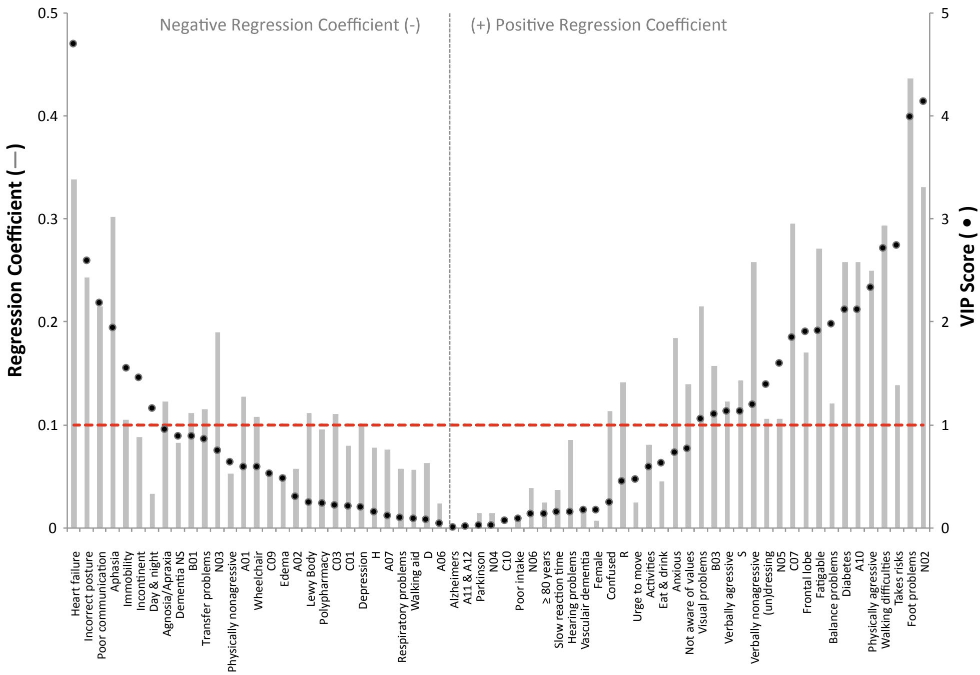


**Figure 3.1** The importance of the patient characteristics (VIP; right axis) in the model and the direction of the association with fall rate (regression coefficient; left axis). The variables of interest are ranked according to their VIP-values and regression coefficients. Variables at the left side of the figure are associated with a lower fall rate, and variables on the right side are associated with a higher fall rate. Characteristics with VIP>1 (above the dotted red line; right axis) are important to the model.

Figure 3.1 shows the importance of the patient characteristics in the model and their relation to fall rate. The most important variables associated with high fall rates (positive regression coefficient, high VIP score) were: foot problems, walking difficulty, balance problems, fatigability, frontal lobe dementia, taking risks, physically aggressive, diabetes and taking drugs for diabetes (A10), use of analgesics (N02), beta blockers (C07) and psycholeptics (N05). Conversely, heart failures, incorrect posture, immobility, incontinence, inability to control day and night rhythm, aphasia and poor communication were associated with low fall rates.

The association between the residents and patient characteristics in relation to fall rate is visualized in Figure 3.2. The position of residents in a given direction in the score plot is influenced by patient characteristics lying in the same direction in the weight plot. Patients

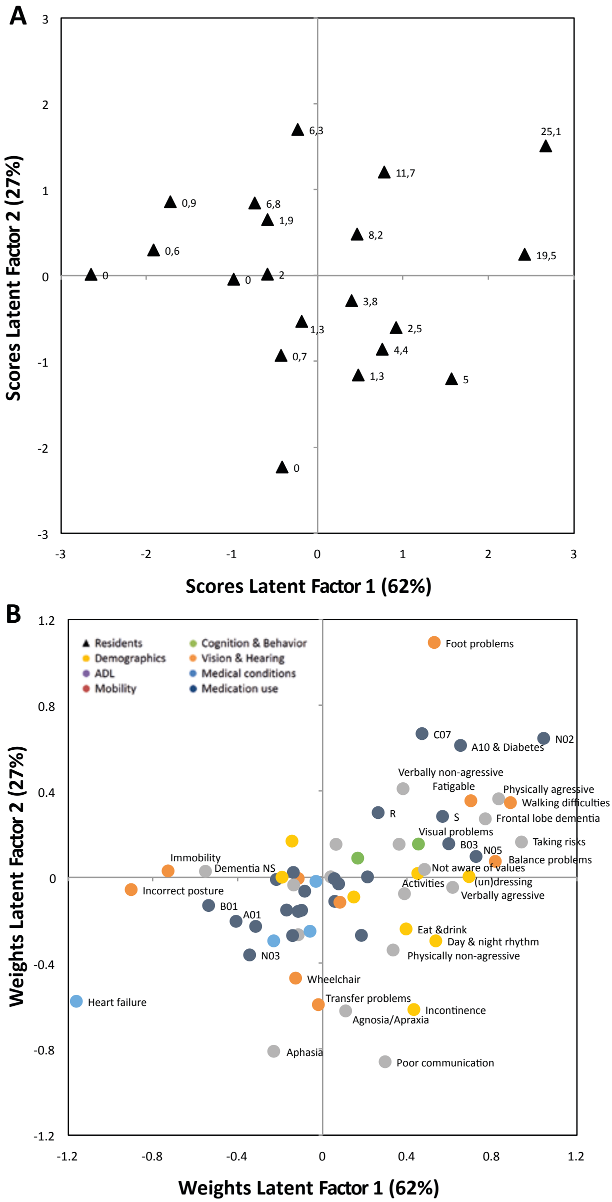


**Figure 3.2** Score plot (**A**) shows the relationship between the residents and displays the fall rate of each resident. Coupled to the weight plot (**B**) the inter-relatedness among the patient characteristics and fall rate is revealed. Patient characteristics and residents at the lower left quadrant are associated with lower fall rates, and variables at the higher right quadrate are associated with higher fall rates.

in the higher right quadrant had overall a high fall rate, whereas persons clustered in the lower left quadrant had a lower fall rate.

## Discussion

The two objectives of the present study were to (1) determine fall rate, fall-related injuries and circumstances of falls, and to (2) examine the relationship between patient characteristics and fall rate in long-term care residents with dementia. The main findings were that 85% of the included residents fell once or more, falls had serious consequences, were most often unwitnessed, and occurred in the bedroom and living room. Furthermore, the model on the relation between patient characteristics and fall rate included three latent factors capturing 96% of the variance in fall rate. Mobility impairments, measures of disinhibited behavior, diabetes, and use of analgesics, beta blockers and psycholeptic drugs were strongest associated with a higher fall rate. In contrast, immobility, heart failure, and poor communication were associated with lower fall rates.

The high fall rate and its serious consequences found in the present study were comparable with the rates reported previously in similar patients and facilities [3,20,21]. However, the high percentage of residents who fell and the serious consequences are alarming and reaffirm the need to increase the efficacy of fall prevention in long-term care residents with dementia.

A large number of falls occurred without the staff being present at the incident. Therefore, for 72% of the falls the exact cause of the fall is unknown. To prevent a fall, it is important to know what happens before and during a fall. Recent studies have shown that falls in common areas in a nursing home occur due to incorrect weight shifting during walking, sitting down and when changing position while standing [22]. As in previous studies, most falls occurred in the bedroom and common areas [23]. To get more insight into the exact circumstances, it may be necessary to monitor common areas and also bedrooms during the entire 24 h period. Monitoring could be accomplished by using optical sensors in combination with learning algorithms that can detect critical events in behavior, e.g. restlessness during sleep. Such monitoring could prevent falls by providing feedback to the patient before making a high risk movement or the monitoring system could signal nursing staff for help [5].

To investigate the relationship between patient characteristics and fall rate, PLS regression was used. The advantages of PLS regression is that it can handle a large number of variables (i.e., patient characteristics,) small sample sizes, and multicollinearity. This analytical approach provides a detailed view of which patient characteristics and in what combinations are important to predict falls. Furthermore, in contrast to other methods used in identify fall risk factors, PLS regressions handles heterogeneous population [19].

The PLS-regression model showed that patients who were still mobile, but had mobility impairments (e.g. foot problems, walking difficulties), had the highest fall rate. Mobility

3

impairments are often related to slow gait, postural instability and increased postural sway, factors exhibited by elderly patients who fall frequently and particularly by those who suffer from cognitive impairments [8,24]. Foot abnormalities or poor footwear are also known to increase fall risk [8]. These findings suggest that there is a need to minimize mobility loss. Recent studies have shown that exercise therapy is effective in improving mobility and fall prevention in residents with dementia [25,26]. Additionally, when such efforts are combined with checking and providing appropriate footwear, e.g. comfortable and firm shoes, anti-slip socks, the fall rate could be lowered.

Results of the present study also showed that residents with frontal lobe dementia and disinhibited behavior are more likely to fall more often than those with other types of dementia. This observation is in contrast with data from earlier studies, suggesting that a diagnosis of Lewy body dementia and vascular dementia was associated with falls [13]. However, it is possible that residents with frontal lobe dementia in combination with disinhibited behavior take more risks in situations that are difficult to cope with and this may consequently lead to a higher fall rate.

Mobility and diabetes were strongly correlated according to the PLS model. Complications from diabetes-induced peripheral neuropathy can reduce sensation at the feet, which in turn affect gait and balance, and ultimately increasing the risk of fall [27,28]. Furthermore, the model showed that analgesics, psycholeptics and beta blockers were also positively associated with fall rate. The weight plot in Figure 3.2 shows that the use of psycholeptics was closely related to measures of disinhibited behavior, because psycholeptics have a calming effect and are therefore often prescribed to residents with challenging behavior (e.g., wandering, aggression) [29]. Analgesics and psycholeptics tend to increase fall frequency and are therefore called Fall-Risk-Increasing-Drugs (FRIDs) [9]. In addition, beta blockers can cause or worsen orthostatic hypertension which is also a known risk factor for falls [30]. The potential beneficial effects of FRIDs and drugs causing or worsening orthostatic hypertension should be weighed against their side effects. Our data suggest that physicians should even more carefully than before consider prescribing such drugs for these patients and when appropriate actually reduce the dose which may lead to a lower rate of falls.

Incontinence is often indicated as a fall risk factor in old adults and is used in many fall prediction tools. However, our results indicate that incontinence in nursing-home residents with dementia does not differentiate between higher or lower fall rates. Moreover, the prevalence of incontinence in fallers versus non-fallers in long-term care residents with cognitive impairments in equally distributed (see also, [12]). The results from studies in community-dwelling old adults or long-term care residents without dementia may therefore not be generalized to the long-term care residents with dementia. Probably, the effects of physical and mental disorders in combination with polypharmacy are so large in long-term care residents with dementia that incontinence is less influential on fall rate.

Current literature is especially focused on factors associated with an increased fall risk, not on factors decreasing the fall rate. Our study showed that heart failure, poor communication and immobility were associated with a lower fall rate. Assessing the relationship between those patient characteristics reveals that the combination of severe mobility problems, cognitive impairments (poor communication), and the existence of factors that make the resident less active (heart failure) cause sedative behavior and consequently decreases the fall rate because residents are less active.

***Limitations***

In the present study, long-term care residents with dementia were recruited from a single nursing home. Although we were able to fit the PLS model satisfactorily to the data, the low participant number limits the generalizability of the results to other patient groups. When more long-term care facilities and residents with dementia are included it might be possible to validate our model in a larger population and develop a more sensitive and sophisticated model of fall risk prediction which could be useful in the clinical setting. Still, our data provide sufficient information for the nursing home staff to start a fall prevention program in patients and environments similar to those in the present study. Further research should seek ways to individualize fall prevention programs more effectively and incorporate in this effort monitoring sensors and individualized fall risk profiles.

Future studies should also consider that patient characteristics such as cognitive status and medication use could change over time. To gain insight into these fluctuations and the effect thereof onto the model, data should be collected over a longer time-span and all changes should be reported accurately, frequently and routinely, which is rarely the case in daily practice of nursing homes. Finally, in addition to the 66 patient characteristics identified in the present study, more transient factors such as changes in mood, sleep, blood pressure, wandering and dehydration could be added to the model to predict fall risk[15].

## Conclusion

Patients with dementia living in long-term care facilities fall frequently. Most of these falls occur unwitnessed. Reduced mobility, cognitive impairment related to disinhibited behavior, diabetes, and the use of analgesics, beta blockers and psycholeptics are associated with a higher fall rate. Moreover, being immobile, inactive and unable to communicate is associated with a lower fall rate. The used analytic approach provided a detailed view of the fall risk factors and their interactions in long-term care residents with dementia and could increase the efficacy of fall prevention programs. To increase the accuracy of fall prediction, future studies will need to identify risk factors that are transiently involved in falls and characterize in more detail the conditions present before and during a fall.

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# CHAPTER 4

# User driven innovation for fall prevention technology: Experiences and requirements from the perspective of nursing home staff

Nienke M. Kosse, Kim Brands, Henrietta Dale, Claudine J.C. Lamoth

## Abstract

**Background**
User acceptance is a major determinant whether the use of a sensor system succeeds or not. Therefore, the first step in the development of a new fall prevention sensor system is to gather knowledge about the user requirements. The aim of this study was to examine the attitude of caregivers towards fall prevention technology. More specifically, we assessed the self-reported knowledge of caregivers towards fall prevention, the opinions about institutional fall prevention policy, the experiences with currently used techniques and determined the demands and expectations for new technology to prevent falls.

**Methods**
Four psychogeriatric wards of a nursing home participated. Qualitative participatory research (semi-structured interviews) was combined with quantitative research (questionnaire) methods to study the attitude towards fall prevention technology. Caregivers from one of the four wards, the intervention ward, were involved in the development of a new sensor system and participated in the semi-structured interviews (n=5). A questionnaire about fall prevention and sensor technologies in health care was distributed to all four wards (n=126).

**Results**
Caregivers found fall prevention very important. Caregivers were satisfied with the available sensor systems (bed-exit alarm and shoe chip), and the notification that was given when a high (fall) risk situation occured. However, the current used sensor needs improvement. Requirements for a new fall prevention system proposed were: notification without delay, an automatically activated sensor system and availability for all residents. Moreover, time, education and support by management were considered important factors for the successful implementation of fall prevention systems.

**Conclusion**
User involvement is crucial to develop and introduce a new technology successfully. Important issues addressed as advantages and disadvantages, and demands create new ideas and optimization opportunities for technology use and development.

## Introduction

The health care sector is experiencing a transformation as a result of the introduction of sensor technologies. Sensor technologies are used in all facets of health care, from monitoring vital signs in a hospital setting to facilitating independent living in the community for elderly. One of the upcoming technologies used in intramural care facilities (e.g. hospitals, nursing homes) are fall prevention sensor systems.

In intramural care institutions, both injurious and non-injurious falls are a frequent occurrence resulting in potentially devastating physical, social and financial consequences [1–3]. Psychogeriatric wards are more regularly confronted with fall incidents and consequently with a larger number of injuries compared to patients of other wards [2]. Therefore, fall prevention is an important topic in health care institutions which provide care for old adults.

The use of sensor systems to prevent falls has been introduced as an alternative for physical restraints, because physical restraints may lead to adverse events such as depression, aggression and absence of freedom, but also to a greater risk of fall-related injuries, breathing difficulties and even early death [4,5]. Due to these negative effects of physical restraints, there is a growing interest in the use of fall prevention sensor technologies.

A wide range of sensor technologies (e.g. wearable and non-wearable technologies using infra-red, position or pressure-sensitive sensors) has been developed in the last decade to reduce the number of falls and fall-related injuries in intramural care facilities. Sensors detect a change in position and might provide feedback to the patients in the form of a sound or verbal instruction, and/or alarm the nurses that a patient is getting out of bed or rises from a chair [5–7]. However, despite the fact that there are various sensor systems on the health care market, there is no consistent evidence that the sensor systems reduce falls in intramural care settings [8].

There are different reasons why sensor technologies for fall prevention may not have the desired effect. One of the possible explanations is the use of sensors that detect only a small area (around a chair or bed) and monitor one event (standing up from a chair or moving out of bed). However, elderly people fall not only in those small areas with one event as trigger. Elderly people also trip and slip in bathrooms, living rooms, hallways and gardens [2,9]. Another limitation of the currently used sensors is that they are not adjusted to the individual patient, while we know that there exists no standard patient. The individual characteristics and the severity of patient's medical condition complicate the effectiveness of the sensor systems [10,11]. New sensor systems need to cover bedrooms, hallways and living rooms, detecting fall risk for every individual patient.

However, technological sophisticated sensors do not offer the full solution. In addition to the capabilities of the sensor system, user acceptance is a major determinant as to whether an intervention succeeds or not [7,12–14]. To date most technological developments aimed at fall prevention are technological driven. For new technologies to be successful in clinical practise a user-driven perspective, in which users participate in the development process, might ensures that technology is compatible with the needs of the end users [15–17].

The purpose of this study was to assess the attitude of caregivers towards fall prevention, fall prevention technology and policy making. We were interested in learning more about the experiences with the currently used sensor systems from the perspective of the users, as well as the specific requirements and expected effects for a new fall prevention system.

## Methods

### *Setting*

The study was executed at four closed psychogeriatric wards of a nursing home in the Netherlands. One of the wards, the intervention ward, actively participated in the development of a new fall prevention system. On the intervention ward, with 20 psychogeriatric residents with severe behavioural problems, worked 19 nursing assistants and five nutrition assistants on a permanent basis; they were complemented with flex workers. In the present study the term caregivers is used to refer to nursing assistants and nutrition assistants working in nursing homes. The other three wards (non-intervention wards) had place for respectively 30, 31 and 32 psychogeriatric residents. On each ward 34 caregivers worked permanently. Other disciplines involved in the wards were nurses, physiotherapists, occupational therapists, physicians and ICT members.

### *Procedures*

*Qualitative research - Interviews*

Qualitative research, semi-structured interviews, with the caregivers from the intervention ward was used to assess in detail their experience with currently used techniques and to specify the requirements for new fall prevention system(s).

Five caregivers from the intervention ward were invited for a semi-structured interview. The interviews were conducted in a closed office and recorded with a digital voice recorder with the caregivers' consent. The respondents were provided with three topics to guide the depth-interviews. The depth-interviews started with questions about the working of currently used sensor systems and notification functions, followed by questions about the advantages and disadvantages of the systems and finally the requirements for a new fall prevention system were discussed. Follow-up questions were asked to deepen or clarify the answers of the caregivers. The interviews lasted approximately 45 minutes.

*Quantitative research - Questionnaire*

A questionnaire was given to the caregivers of the four psychogeriatric wards to investigate the attitude towards fall prevention and policy making, to assess the experiences of the currently used sensor systems and examine the requirements and expected effects of a new fall prevention system.

A special questionnaire entitled ‘Caregiving’ was constructed out of two Dutch questionnaires [18,19]. The questions related to fall prevention and/or sensor technologies in health care were selected from the two questionnaires. Some of these selected questions were adapted to the nursing home’s situation. The first questionnaire used was ‘Course in fall prevention for employees in nursing homes’, designed to evaluate the influence of a fall prevention course on the knowledge of the caregivers [18]. The questionnaire asked about the degree of agreement (1 to 9) on statements regarding different aspects of fall prevention [18]. Eight statements were selected for the questionnaire ‘Caregiving’, asking about the attitude towards fall prevention (3 items), and the self-reported knowledge towards fall prevention (2 items) and fall risk factors (3 items).

The second questionnaire used was the ‘Experiences of nurses and nursing assistants with new technologies in healthcare’, designed to discover the ideas of nurses and caregivers concerning new technologies [19]. The questionnaire detects the threats, opportunities and needs that caregivers experience in using these technologies [19]. For the present study the movement and notification functions were included in the questionnaire ‘Caregiving’. The experienced effects of the used technologies and the required and expected effect of a new technology on the quality of care (4 items), amount of work (2 items) and the quality of work (3 items) were questioned. Every item was rated on a 5-point scale ranging from a negative effect (-2 or -1), no effect (0) or a positive effect (1 or 2) [19]. Additionally fourteen possible requirements to introduce a new technology were listed. Per requirement the health care worker had to indicate if it was not needed, desirable or absolutely necessary.

Four questions about the policy making of the organization concerning new technologies and involvement of the caregivers in the decision-making process were changed and added to the questionnaire in the form of a statement. The caregivers were asked how much they agreed with the statements scoring 1 to 9 [18,19].

The final questionnaire ‘Caregiving’ included 16 questions addressing the following items: characteristics of the caregivers, attitude towards fall prevention, the self-reported knowledge towards fall prevention and fall risk factors, the opinions about institutional fall prevention policy and the involvement of the caregivers in policy making, the experiences with currently used techniques, requirements and necessary conditions for using a new fall prevention device, and the effects and expected effects of current and new sensor systems on the quality of care and work.

Since three wards were not actively involved in the development of the new fall prevention system, the questions about the expectations of the new fall prevention device were excluded for those wards. Those three wards were informed about the development of the fall prevention system in a short introduction accompanying the questionnaire.

*Data analyses*
An inductive method of analysis was applied, in which interview transcripts were read and coded. The codes were grouped into the three pre-developed themes: the current used sensor systems, the advantages and disadvantages of the current used sensor systems and the requirements for a new sensor system.

Data from the questionnaire were analysed with IBM SPSS statistics version 20.0. Descriptive statistics (mean, standard deviation, percentage and range) were calculated for the characteristics of the caregivers on the wards. The data from the questionnaires were analysed with the Mann-Whitney U test to control for differences between the intervention ward and the wards without intervention. A p value of $< 0.05$ was considered statistically significant. For the items with no significant difference, descriptive statistics are presented for all wards together. The items with a significant difference are presented separately for the intervention ward and the non-intervention wards.

***Ethical considerations***
The study was approved by the local Ethical Committee of the center of Human Movement Sciences Groningen, University Medical Center Groningen.

## Results

***Qualitative research - Interviews***
Interviews were obtained with five caregivers from the intervention ward, three nursing assistants and two nutrition assistants (mean age 49.4 years, range 36 - 60).

*Currently used systems*
Three different sensor systems (Table 4.1) were used on the psychogeriatric ward:

- a bell system, residents can ask for help with a button next to their bed, the bedroom or in the bathroom.
- a bed-exit alarm (Optiscan ®) for residents with a high risk of falling. The alarm goes off when the resident gets out of the bed.
- a shoe chip, for residents who are walking away from the ward. When a resident with shoe chip walks through certain doors an alarm is triggered.

Notifications were received on two different pagers, one for the bed-exit alarm and the bell system, and another for the shoe chip. On the small pager screen, the room number of the resident who needs assistance appears or the door number of the door where a resident is walking through. The bell system is rarely used by the residents on the intervention ward; the residents are not able to use the system because of their cognitive problems. Therefore, the bed alarm system and shoe chip alarm were further discussed in the interviews.

The currently used devices are mainly associated with positive effects. As two of the caregivers said in their interview:

> 'I could not do without (the bed-exit sensor)'

> 'I do not know otherwise, I've always worked with this system (bed-exit system) and I don't know other systems. So for me, this is handy.'

*Advantages and disadvantages*

There are benefits and disadvantages noticed by the caregivers throughout the time the sensor systems were used (Table 4.1). The caregivers were content with the notification function of the sensor systems. The alarm goes when an intervention is needed and it is clear to which room or door they have to go. However there are also some disadvantages about the technologies. The alarm systems are delayed between the event (getting out of bed or walking through the door) and the signal given on the pager:

> 'I always start to walk at the first beep, and I walk fast, but the resident is already moving through his room when I arrive. It (the bed-exit alarm) notices too late'.

Another problem is the activation of the bed-exit alarm:

> 'For us it is a routine to turn on the bed-exit alarm when we put the residents to bed at night, but staff who is not familiar on the ward can forget to turn the alarm on.'

The bed-exit alarm is not available for all residents. The system is only used for the residents who have a high fall risk at night, and unfortunately it often appears that residents have to fall first before the need for an alarm is considered.

> 'It would be nice if all residents were connected to a new fall prevention system. Now the choice to use a bed-exit alarm is often made after a fall incident, so when the steed is stolen, the stable-door is locked.'

Sometimes the sensors give false alarms, for example residents are not walking through a door or a sheet has fallen off the bed and causes an alarm. False alarms can cause desensitization, and this occurs especially in the early morning on the ward. During the shift change, the caregivers do not immediately react to the alarm.

**Table 4.1** Interview outcomes: experiences of current used systems and requirements for a new fall prevention system.

| **Current used systems** | |
|---|---|
| Bell system for residents asking for help | |
| Bed-exit alarm (Optiscan ®) for residents with a high risk of falling | |
| Shoe chip for residents who walk away from the ward | |
| **Advantages** | **Disadvantages** |
| The notification<br>'you know there is something wrong' | The alarm signal is delayed<br>The resident causing the alarm is unknown |
| Notification by room number or door | False alarms, due to:<br>· blankets falling of the bed<br>· curtain moved by the wind<br>· residents walking through a door under supervision<br>· no cause of alarm<br>The bed-exit alarm is not automatically activated<br>The bed-exit alarm is not available for all residents |
| **Requirements for a new fall prevention system** | |
| Notification by:<br>· location of the resident<br>· name resident<br>Early detection of fall risk<br>No delayed notification | Automatically activated<br>Available for all residents<br>The system needs to be supported by all members of the team |

*Requirements for a new fall prevention system*

Table 4.1 lists the requirements for a new fall prevention system. The caregivers like to know which resident needs help and where on the ward they have to go. An early alarm must be provided, preferably before the high fall risk situation occurs.

> 'I would almost say that if a resident is tossing and turning in his bed it must be registered'

Furthermore, the fall prevention system must be available for all residents on the ward and automatically activated.

> 'It is in our routine to activate the alarm at night when we bring the residents to bed, but for people not familiar on the ward or who haven't the routine to turn on the switch it would be useful to have it (bed-exit sensor) automatically regulated.

The support of all colleagues on the ward is required to make the introduction of a new technology successful:

‘I think it is important that everyone supports and co-operates with the new system. […] If one person thinks the system is nothing for him/her and walks away, the system won’t work of course.’

### *Quantitative research - Questionnaire*

The questionnaire was handed out to all 126 caregivers working permanently on the four psychogeriatric wards. Forty-two questionnaires were filled in and returned to the researchers, a total response of 33.3%. The mean (SD) age of the respondents was 41.1 (9.6) years and all the respondents were women. The characteristics of the caregivers for the intervention ward and the non-intervention wards are described in Table 4.2. There was no significant difference between the characteristics of the caregivers on the wards.

**Table 4.2** Characteristics of the caregivers who returned the questionnaire.

| | Intervention ward | Non-intervention wards |
|---|---|---|
| Response (%) | 70.8 (n = 17) | 24.5 (n = 25) |
| Age (mean ± SD) | 42.8 ± 9.4 (range 23-59) | 39.6 ± 9.8 (range 20-55) |
| Gender, female (%) | 100 | 100 |
| Working hours a week (mean ± SD) | 20.4 ± 5.6 (range 12-30) | 21.0 ± 8.8 (range 0-32) |
| Years’ work experience (mean ± SD) | 14.5 ± 8.9 (range 0-26) | 15.6 ± 9.1 (range 0-32) |



*Attitude towards fall prevention and policy making*

The results of the questionnaire are presented in Table 4.3. More than 95% of respondents agreed or agreed strongly that it is important to give attention to fall prevention, 64.3% think falls are preventable in the elderly and 81% of the caregivers are already doing a lot on their ward to prevent the residents from falling. However, the caregivers are not convinced of their knowledge about fall risks and prevention. Only 47.5% say that they know what to do to prevent residents from falling, 73.9% knows the causes of fall incidents and 61.9% can list the fall risk factors on their ward.

The majority (59.5%) of the caregivers on the four wards found the policy with regard to the use of new techniques and technologies of their organization progressive. Nevertheless, the wards disagreed about the policy making and the way caregivers are involved in the decision making process. More than 82% of the caregivers on the intervention ward judged the policy of the organization with respect to the use of new techniques and technologies to prevent falls as good, compared to 50% on the non-intervention wards. The opinion about the involvement of staff in introducing new techniques and technologies differed also between the wards: 70.6% on the intervention ward felt that they were involved in the right way compared to 32% on the non-intervention wards. The largest contrast between the wards was seen in the involvement of staff in decision-making in introducing new

**Table 4.3** The staffs' perspective: effects of current used devices, requirement and expectations for a new device.

| | Current devices (n = 42) | | | | Requirements of a new device (n = 42) | | | Expectations of the new device (n= 17) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Neg effect | No effect | Pos effect | Mean effect | Not important | A bit important | Important | Neg effect | No effect | Pos effect | Mean effect |
| **Quality of care** | | | | | | | | | | | |
| Quality of care given to de patient | 0 | 2.4 | 97.6 | ++ | 0 | 7.1 | 92.9 | 0 | 5.9 | 94,1 | ++ |
| Quality of life of the patient | 0 | 4.8 | 95.1 | ++ | 0 | 4.8 | 95.2 | 0 | 5.9 | 94.1 | ++ |
| Independence of the patient | 4.9 | 31.7 | 63.4 | + | 2.4 | 17.1 | 80.5 | 6.2 | 18.8 | 75.0 | ++ |
| Safety of the patient | 0 | 0 | 100 | +/++ | 0 | 2.4 | 97.6 | 0 | 0 | 100 | ++ |
| **Amount of work** | | | | | | | | | | | |
| Cost of care | 20.5 | 23.1 | 56.4 | + | 38.5 | 33.3 | 28.2 | 47.1 | 17.6 | 35.3 | -- |
| Number of patients that can be cared for | 5.0 | 27.5 | 72.5 | + | 14.6 | 36.6 | 48.8 | 5.9 | 23.5 | 70.6 | + |
| **Quality of work** | | | | | | | | | | | |
| Physical workload | 28.6 | 26.2 | 45.2 | + | * | | | 64.7 | 0 | 35.3 | - |
| *Intervention ward (n = 17)* | | | | | 0 | 17.6 | 82.4 | | | | |
| *Non- intervention wards (n = 25)* | | | | | 0 | 0 | 100 | | | | |
| General workload | 24.4 | 24.4 | 51.2 | + | * | | | 47.1 | 0 | 52.9 | + |
| *Intervention ward (n = 17)* | | | | | 6.3 | 31.3 | 62.5 | | | | |
| *Non- intervention wards (n = 25)* | | | | | 0 | 4.0 | 96.0 | | | | |
| Job attractiveness | 9.8 | 34.1 | 56.1 | + | 5.0 | 12.5 | 82.5 | 11.8 | 17.6 | 70.6 | ++ |

*significant difference ($p < 0.05$) between the intervention ward and the wards without intervention according to the Mann Whitney test
neg = negative, pos = positive, ++ strong positive, + positive, 0 no effect, - negative effect, -- strong negative effect

techniques and technologies: 81.2% of the caregivers on the intervention wards found that they took part in the decision-making compared to 4% on the non-intervention wards.

*Experiences of the current used system*

Table 4.3 gives an overview of the opinion of the caregivers concerning the quality of care, amount of work and quality of work. The current used systems have a strong positive effect on the quality of care, quality of life, independence and safety of the residents. The technology has a positive effect on the number of patients that can be cared for and the cost of care. The quality of work is for half of the caregivers positively influenced by the current used sensor systems. Although the other half of the caregivers found that the sensor systems had a negative or no effect on the physical and general work load.

The requirements to introduce the fall prevention system are shown in Table 4.4. Support from all people who are involved on the ward is necessary, including the management team, supervisors, colleagues and other disciplines involved on the ward, the technical department, the residents and their legal representatives. To make the system work, it is important to give good education to the caregivers, give them time to get used to the system and time to practice with the device.

**Table 4.4** Requirements to introduce a new system obtained from the questionnaire.

| **Requirements** | |
|---|---|
| Support from: | Extra education in knowledge and skills |
| · other members in my team | Self-confidence about working correctly with the device |
| · other disciplines | Time and space to get used to the system |
| · the direct supervisor | Good technical support |
| · clients and/or legal representatives | |
| · the management team | |

4

## Discussion

In the present study we assessed the attitude of caregivers towards fall prevention, fall prevention technology and policy making. We were interested in the experiences with the currently used sensor systems from the perspective of the users, as well as the specific requirements and expected effects for a new fall prevention system.

Fall incidents are a big problem in nursing homes, especially on psychogeriatric wards. Caregivers working on a psychogeriatric ward in a nursing home strongly agree that fall prevention is necessary and that falls are preventable. However, less than 50% of the caregivers reported that they know what to do to prevent resident from falling. Making caregivers aware of the fall hazards on their ward can reduce fall incidents [20] and generate more user-driven ideas to make a highly effective fall prevention system.

Caregivers were satisfied with the available sensor systems (bed-exit alarm and shoe chip) on the psychogeriatric ward. The sensor systems gives a notification when there is a high (fall) risk situation for the residents and the message on the pager shows clearly were to go. However, there are still improvements needed. The requirements for a new fall prevention system arised from the disadvantages of the current used sensor systems. The caregivers like to be notified earlier about a high fall risk and without delay, with the location and the name of the resident, preferable a system automatically activated and available for all residents. The caregivers expect from a new system that it will increase the quality of care and the quality of life of the residents. These findings highlight the need to increase the fit between users and technology through co-creation. Technological developments need to be driven from the user's perspective.

The involvement of users does not stop after the design phase of the product, but users have to be involved into the introduction and implementation phases [21]. Users need to start to work with the fall prevention system. However, caregivers can have a negative attitude towards technologies, poor skills and knowledge about what could be done with the available technology, which prevents them from using the technology. Therefore, identifying the barriers keeping caregivers from using new technologies could help to better design the system and to optimize education strategies and programs. When a system is developed and ready to use, caregivers need to learn how to manage the new system. Time and education has to be provided to get used to the fall prevention system and to learn how to work effectively and safely with the system [14,22–24]. Increasing knowledge and experiences with technologies will provide acceptance of using technologies [25,26]. Therefore, it is not only important to involve the caregivers in the development process of a new system but technology development and the use of technologies need to be admitted to the educational programs of students following a health care study. For the caregivers who finished their studies the use of technology must be added into the in-service training they receive. Creating optimal conditions to acceptant a technology and developing user required technologies will increase the successfulness of technology interventions into health care.

The development of a fall prevention system from a user perspective requires the involvement of users themselves [27]. Users know the advantages and disadvantages of the current used technologies and can indicate solutions and optimization opportunities for a new device. Users generate ideas from their wishes, demands and expectations for a new and innovative product.  The group investigated caregivers was small and coming from a single nursing home, which makes the results less generalizable. However, this study makes clear that involvement of the users during the development process of a new technology is important. The caregivers involved in the development process were highly motivated and liked to contribute to the fall prevention system. When a health care system is developed the designer has to take into account that health care facilities differ in users' characteristics, skills and working environment [21]. In this study the user requirements from the intended users of the new technology are examined [19].

Co-creation is recommended, where designers, managers and caregivers listen to the ideas of each other to develop an optimal working system in clinical practice [16,28].

The results of this study showed that user involvement is crucial to get a cooperative attitude from caregivers. Almost three-quarter of the caregivers from the intervention ward filled in the questionnaire compared to a quarter of the caregivers from the wards without intervention. Where the caregivers from the intervention ward felt they were involved in the organizational decision-making process about technology use and the caregivers on the non-intervention wards felt that they were not involved at all. Besides the more cooperative attitude from the caregivers on the intervention ward they were more willing to invest into a new technology when this technology would be introduced on the ward. The caregivers of the intervention ward responded positively and productively to the involvement into the development process [9]. Thus, involving users establishes a positive attitude and the willingness to invest into a new system [22].

## Conclusion

Managers, designers and researchers developing and implementing new technologies into health care settings need to be aware of the user's characteristics, wishes and demands. In the current study, nursing home staff provided information about the experiences of current used technology and the requirements and expectations for a new fall prevention system. Users addressed issues and ideas strongly related to the daily use of technologies, like the occurrence of false and delayed alarms and the wish for an automatically activated fall prevention system available for all residents. Additionally, optimal conditions, including support and education, have to be created to develop and implement a new sensor system with success.

User involvement appeared crucial to motivate caregivers to take part in research and create the willingness to invest into a new technology. The knowledge of users is essential in the development and introduction of new technologies. The next step is to monitor and evaluate the development, introduction and implementation of the new fall prevention system continually. The view of caregivers may change over time and the impact of the system may change wishes and demands.

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4

# CHAPTER 5

# Validity and reliability of gait and postural control analysis using the tri-axial accelerometer of the IPod Touch

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## Abstract

Accelerometer-based assessments can identify elderly with an increased fall risk and monitor interventions. Smart devices, like the iPod Touch, with built-in accelerometers are promising for clinical gait and posture assessments due to easy use and cost-effectiveness. The aim of the present study is to establish the validity and reliability of the iPod Touch for gait and posture assessment. Sixty healthy participants (aged 18-75 years) were measured with an iPod Touch and stand-alone accelerometer while they walked under single- and dual-task conditions, and while standing in parallel and semi-tandem stance with eyes open, eyes closed and when performing a dual task. Cross-correlation values (CCV) showed high correspondence of anterior-posterior and medio-lateral signal patterns (CCV's≥0.88). Validity of gait parameters (foot contacts, index of harmonicity, and amplitude variability) and posture parameters (root mean square of accelerations, median power frequency (MPF) and sway area) as indicated by intra-class correlation (ICC) was high (ICC=0.85-0.99) and test-retest reliability was good (ICC=0.81-0.97), except for MPF (ICC=0.59-0.87). Overall, the iPod Touch obtained valid and reliable measures of gait and postural control in healthy adults of all ages under different conditions. Additionally, smart devices have the potential to be used for clinical gait and posture assessments.

## Introduction

The aging population is expanding and is associated with many health problems and the additional health care costs. Falls and fall-related injuries are critical problems in old adults. One out of three community-dwelling old adults falls at least once a year [1]. Unfortunately, those fall incidents have often serious consequences like bruises, fractures, decreased mobility, social isolation or even early death [2]. To maintain the quality of life for old adults, it is important to recognize an increased fall risk in time and to offer fall prevention intervention(s) before a (first) fall takes place [3]. One of the main reasons that old adults fall are mobility impairments. Accordingly, in the geriatric clinic, analysis of gait and postural control is becoming increasingly important for diagnostic purposes. Daily practice of an outpatient geriatric department is confronted with a high rate of frail elderly patients. These patients are characterized by a combination of physical, mental and social problems, use of polypharmacy and consequently high fall risk [4,5]. An instrument that could quantitatively and objectively evaluate and assess deterioration in balance and gait, and monitor the impact of mobility improving interventions is thus of great importance.
A number of clinical instruments are available to quantify fall risk in old adults, such as questionnaires, fall diaries and physical performance tests [6,7]. Due to their influence on fall risk, gait and posture assessments are often included in those clinical instruments. However, the currently accepted clinical tests provide only a global assessment of balance and gait ability, and suffer from limitations including ceiling effects and limited precision to detect small changes in balance and gait ability [8,9].

Instrumented recordings can provide detailed information about changes in gait and postural control due to changes in task conditions, ageing and/or pathology [5,10,11]. A number of sophisticated ambulant systems are available for research purposes, such as pressure sensitive soles or mats, stand-alone 3D accelerometer and gyroscope sensors. By now an extensive number of studies have shown that parameters extracted from these signals, provide insight into motor control and are sensitive to detect postural differences between patient groups, age groups and task condition and can even predict falls [12–16]. However, main drawbacks for the clinical use of these systems is that they are quite expensive and they require specialized research staff to collect and analyse the data.

The recent rapid development of off-the-shelf mobile devices and smartphones provide an interesting alternative for motion analysis in the clinic, as these smart devices are nowadays standard equipped with inertial sensors, such as tri-axial accelerometers. Consequently, it may be possible to use the acceleration signals collected by smart devices, to calculate gait and posture parameters. At this point, if the accuracy and reliability of these smart devices is comparable to the current used stand-alone accelerometer-based research methods, this could provide new prospects of using the accelerometer embedded in smart devices in clinical motion analysis. First, smart devices are getting cheaper and many people use them on daily basis, they are lightweight and easy to handle. Second, data can be transmitted wireless over long distances and from remote locations without retrieval of the device, which provides the opportunity to send data directly to an external personal computer which clinicians or researchers can assess. Thirdly, applications for motion recording and analysis can be programmed according to the needs of the end-user, researcher and/or clinician. Finally, data of gait and posture can be combined automatically with data from questionnaires, clinical tests and drug monitoring. Using a single device allows the clinician to assess deterioration in postural control and gait and to monitor the impact of mobility improving interventions.

The validity and reliability of available stand-alone accelerometer systems for motion analysis have been determined in numerous studies, measuring gait and posture parameters [17–19]. Although motion analysis using smart devices is an emerging and promising area, only a few studies exist that assess gait and postural control. First results show good test-retest reliability between data collected by a smartphone (Xperia S0-01B, Sony Ericsson) and by a stand-alone accelerometer unit for walking of healthy adults, (intra-class correlation between 0.75-0.91) [20], and also when comparing data collected during standing from an iPod Touch with that of a force plate (r ≥0.82) [21].

Validity and test-retest reliability might be different for different task conditions and/or for different individual groups. Therefore, the purpose of this study was to demonstrate proof of the concept that the accelerometer embedded in the iPod Touch can be used to accurately and reliably collect signals of anterior-posterior and medio-lateral trunk acceleration for calculation of gait and posture parameters in healthy young, middle aged and older adults during the performance of different walking and balance tasks. More specifically age effects as well as task effect were studied. Participants between 18 and 75 years were instructed to walk with and without performing a cognitive dual task, and we challenged their standing posture by asking them to stand parallel as well as in semi-tandem stance with eyes open, eyes closed and while concurrently performing a dual task.

## Materials and methods

### *Participants*

The study population consisted of 22 young healthy adults (26 (3.9) years; 50% male), 15 middle aged healthy adults (45 (6.7) years; 67% male) and 23 older healthy adults (65 (5.5) years; 30% male) recruited from the community. Participants between 18 and 75 years old were included if they had no orthopaedic or neurological problems and used no medication that might affect gait or postural control.

The Ethical Committee of the Center of Human Movement Sciences at the University Medical Center Groningen approved the research proposal and all participants signed written informed consent.

### *Instrumentation*

To assess trunk accelerations during walking and standing the iPod Touch G4 (iOS 6; 123x59x6 mm, 88 gram, Apple Inc.), which has a built-in tri-axial acceleration sensor, was used. To collect and store the accelerometer data, a custom made application 'iMoveDetection' was installed on the iPod. The raw acceleration data was recorded at a sample frequency between 88 and 92 Hz. After each measurement, the raw data was saved on the device and send to a remote server through WIFI communication, further analysis occurred offline. To investigate the validity of the data collection with the iPod, trunk accelerations were at the same time measured with a stand-alone accelerometer unit, the DynaPort®hybride unit (56x61x15 mm, 54 g; McRoberts BV, The Hague, the Netherlands), which was considered the 'golden standard' in the present study. The Dynaport unit consists of tri-axial accelerometers collecting data at 100 Hz and stores the data on a SD card.

### *Procedure*

The accelerometer unit was fixed with an elastic belt near the level of lumbar segment L3 over the clothes. The iPod was firmly attached with Velcro to the stand-alone accelerometer.

To assess the validity of the iPod to quantify gait and postural control, the participant performed walking and standing tasks. In the walking task the participant walked for 3 minutes at a self-selected speed up and down a 10m long course with a 1m curve, under single and dual task condition. The dual task consisted of a letter fluency test; the participant had to name as many words starting with a predefined letter (D-A-T) as they could within 1 minute [22].

Participants performed two standing tasks, (1) parallel stance and (2) semi-tandem stance. Each standing task consisted of three conditions, which were performed for 1 minute: eyes open, eyes closed, standing while concurrently performing a dual task. The dual task was the same as during walking but now with the letters 'G' and 'P'.

To investigate the test–retest reliability of the iPod, the 3 minute walking test under single task condition and the standing parallel and semi-tandem with eyes open were performed twice.

The tasks (walking, standing) were randomized, and within one task all conditions were randomized for each participant.

### *Data analysis*

Anterior-posterior (AP) and medio-lateral (ML) trunk acceleration signals of the iPod and of the accelerometer unit were analysed using custom-made software in MATLAB (version 2012b, The MathWorks Inc., Natick, MA, USA). The sampling rate of the iPod was not constant; therefore the data were interpolated to get a constant sampling of 100 Hz.

First, a cross-correlation analysis was performed between the two devices, respectively for the AP and ML accelerations, for each subject and each trial. We were specifically interested in the maximal correlation between the signals and the associated time lag, to compare the similarity of the pattern of the signals of the two measurement devices. The cross-correlation value between the signals was calculated at all possible time lags (of 0.01 s) for all trials. The time lag associated with the maximal cross-correlation was used to synchronise the data.

### *Gait analysis*

Prior to the gait analyses the iPod and accelerometer unit signals were detrended and filtered (4th order Butterworth; cut-off frequency 20 Hz).

Due to their relevance in clinical research the following gait parameters were obtained from accelerometer data from the walking trials: foot contacts (FC), the Index of Harmonicity (IH), and the amplitude variability (AmpVar).

From FC conventional step parameters are derived, such as step time or stride time and the variability of step or stride time. Therefore, an accurate detection of the FC is important. FC were detected based on the minima of the smoothed (Butterworth filter, 4th order; cut-off frequency 2 Hz) AP signal. Using these detected peaks as reference, the FC (nearest peaks) were determined in the unfiltered signal. To assess the agreement between the detection of the FC by the iPod and by the accelerometer unit data, the mean difference of number of samples between the detected FC was calculated for each trial.

The IH was calculated for the individual AP and ML accelerations using spectral analysis and is considered an indicator of the smoothness of the acceleration patterns [23]. The power spectrum of the acceleration data of ML and AP accelerations was estimated by means of a discrete Fourier transform. The peak power of the first subsequent 10 harmonics was estimated. The IH was defined as:

$$\text{IH} = \frac{P_1}{\sum_{i=1}^{10} P_i}$$

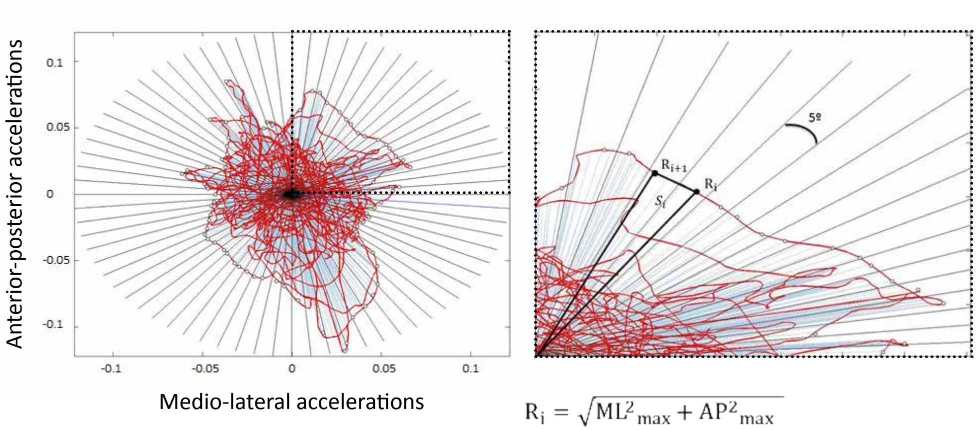
where $P_1$ is the power spectral density of the fundamental frequency (first harmonic, stride frequency), and $\Sigma\, P_i$ the cumulative sum of power spectral density of the fundamental frequency and the first 10 super-harmonics. A power ratio of 1 indicates that accelerations are perfectly harmonic. In view of possible drift, the power spectral density of each peak was calculated within the frequency bands of + 0.1 and − 0.1 Hz of the peak frequency value. All power spectral densities were normalized by dividing the power by the sum of the total power spectrum, which equals the variance.

Finally, the AmpVar provides an indication of the between gait cycle variability. First all strides were time normalized to 100 data points per stride (100% gait cycle). Point-by-point standard deviations across the normalized strides were calculated and averaged over these normalized time points, representing the variability between stride cycles for each trial.

### ***Posture analysis***

Prior to the analyses of the AP and ML signals during the standing tasks, a high pass fourth order Butterworth filter was applied with a cut-off frequency of 0.3 Hz to correct for slow drifts during standing, Additionally, a third-order Savitsky-Golay smoothing filter with frames of 41 points to eliminate low amplitude measurement noise was applied.

The root mean square (RMS, $m/s^2$) indexed the variability of the accelerations of body sway in AP and ML accelerations. To assess the frequency content of the AP and ML acceleration signals, the frequency content of the time-series was determined by calculating the median of the total power of the signal (MPF, Hz). The MPF was derived from the power frequency spectrum estimated by Welch's method, using a Hamming window without overlap. To quantify the entire acceleration path the Sway Area (SA, $m^2/s^5$) was calculated. The SA is the area enclosed by the acceleration path in the AP-ML plane during the one minute stance. To obtain a mean value for the SA, first, the AP-ML path diagram was divided into 72 segments of angles of 5° each (see Figure 5.1). From the AP and ML signals the resultant vector *R* was calculated. In each segment the largest resultant vector ($R_i$) was determined. The area enclosed by two subsequent maximal $R_i$ of a segment was calculated ($S_i$). By summing up the 72 segment areas the SA is approximated [24].




$$R_i = \sqrt{ML^2{}_{max} + AP^2{}_{max}}$$

$$S_i = \frac{R_i * R_{i+1} * \sin(\emptyset)}{2} \qquad SA = \sum_{i=1}^{m-1} S_i$$

$$m = 72, \emptyset = 5$$

**Figure 5.1** On the left side, a presentation of the total sway area (SA) is plotted for the anterior-posterior (AP) and medio-lateral (ML) accelerations. On the right side, a close-up of the upper right quadrant of SA, illustrating the calculation of the SA. SA = sum of $S_i$ based on the largest resultant vectors ($R_i$, $R_{i+1}$) for each segment.

### ***Statistical Analysis***

To get insight into the individual spread of the measurement error between the iPod Touch and the accelerometer unit the computed gait and postural parameters were analyzed using Bland-Altman tests. In Bland-Altman plots, the average value for each pair of measurement is plotted against the mean difference between the two values of the two measurement devices of individual data of all conditions within a task. In addition, the upper and lower limit of agreement as 1.96 x standard deviation, the coefficient of agreement (%) as the limit of agreement expressed as a percentage of the mean of the value of the two devices, and the coefficient of variance (%) as the standard deviation divided by the mean value of the two measurement devices were calculated.

The validity of the gait (IH, AmpVar ) and posture parameters (RMS, MPF, SA) derived from the signals of the iPod and accelerometer unit, was assessed using a case 3 intra-class correlation [25] as:

$$\text{ICC (3,1)} = \frac{(\text{BMS} - \text{EMS})}{\text{BMS} + (k - 1)\text{EMS}}$$

where, BMS is the mean squares between measurements of the two devices, EMS is the within measurements mean squares of error and k is the number of devices (k=2).

The test-retest reliability of the gait and posture parameters obtained from the iPod accelerometer signal was examined by calculating the case 2 intra-class correlation[25] between measurements of the same condition (e.g. walking under single task condition, parallel stance and semi-tandem stance with eyes open) as:

$$\text{ICC (2,k)} = \frac{(\text{BMS} - \text{EMS})}{\text{BMS} + (\text{JMS} - \text{EMS})/n}$$

where, JMS is the mean squares between the devices and n is the number of measurements (n=2).

ICCs were calculated, separately for all conditions and for age categories, using MATLAB software (version 2012b, The MathWorks, Inc., Natick, MA, USA). The following guidelines were used to interpret the ICC values: >0.80 represents excellent reliability, 0.60–0.80 good reliability 0.40-0.60 moderate reliability and <0.40 poor reliability [25]. A p value of < 0.05 was considered statistically significant.

## Results

### ***Gait parameters***

Averaged across participants, mean walking speed was 1.2 (0.12) m/s during walking without dual task and 1.1 (0.21) m/s during walking with a cognitive dual task. Data of two trials in each condition were excluded because the data were not completely recorded by the iPod or the accelerometer unit due to technical reasons.

The pattern of time series of the AP and ML accelerations were very similar (see Figure 5.2 for a representative example) as also indicated by the high (≥ 0.90) cross-correlation values between the signals of the two devices for AP as well as ML accelerations in both walking conditions. The associated mean time lags were 0.3 s (single task) and 0.4 s (dual task). Table 5.1 shows the cross-correlation values and corresponding time lags for both walking conditions. The FC detected based on the iPod and accelerometer unit signals differed on average 0.02 s (2 samples) for both single and dual task conditions.

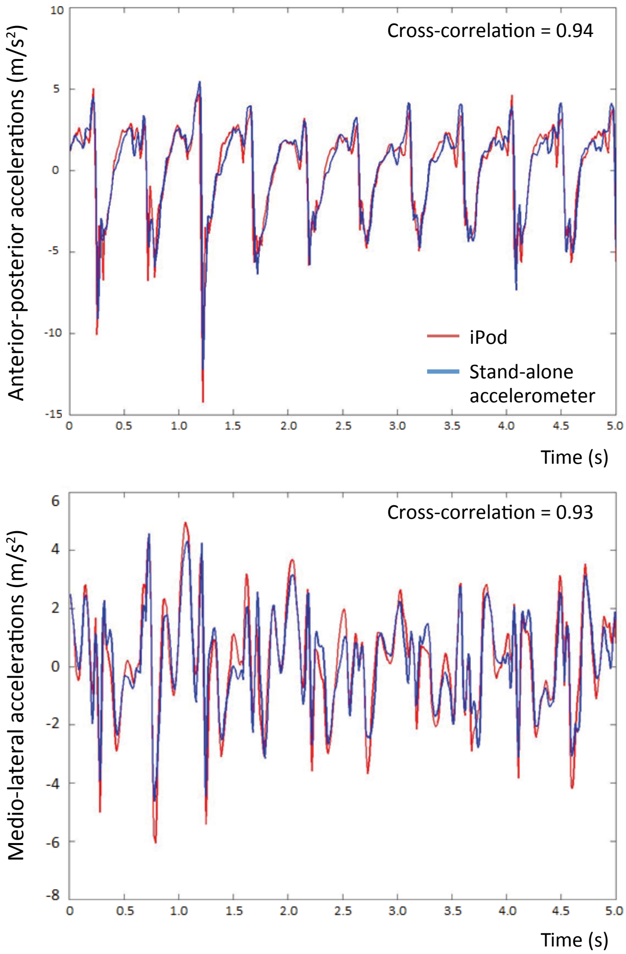



**Figure 5.2** Synchronised iPod (red line) and stand-alone accelerometer (blue line) acceleration signals in anterior-posterior (AP) and medio-lateral (ML) planes during walking. The cross-correlation value is displayed in the right corner of the plots.

Figure 5.3 represents Bland Altman plots for the IH and the VarAmp. Overall, the measurement error between the two devices was very low as indicated by mean values close to zero and the small limits of agreement. However, in two participants the difference between the devices was higher than might be expected based on the other participants' measurements, causing the outliers in the IH and VarAmp. In line, the RPC% and CV of these participants were also low.

Validity and reliability were high for the IH and AmpVar for AP and ML accelerations in both walking conditions indicated by ICC values between 0.85 and 0.98. There were no differences in accuracy or reliability found for the three age categories. Table 5.2 shows the ICCs and confidence intervals per condition.

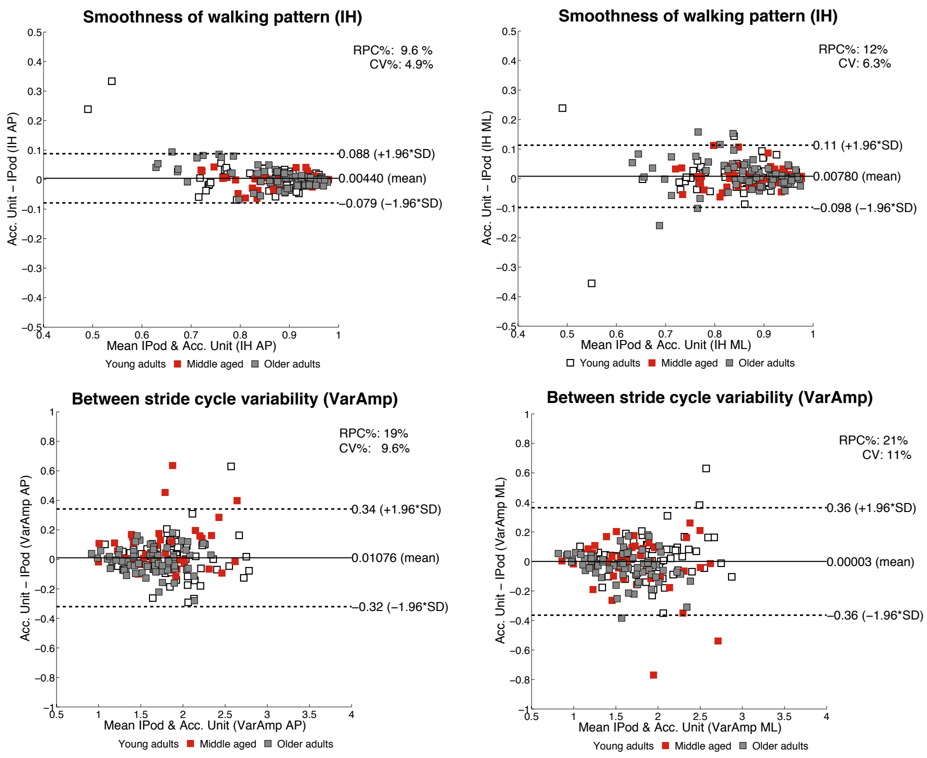



**Figure 5.3** Bland-Altman plots of the mean of the measurements of the iPod and the stand-alone accelerometer (Acc.Unit; x-axis) against the difference of the measurement of individual participants, for the index of harmonicity (IH) value and the variability between gait cycles (VarAmp) during walking in anterior-posterior (AP) and medio-lateral (ML) plane. White squares represent young adults, red the middle-aged adults, and grey the older adults. RPC% is the reproducibility coefficient as % of the mean. CV is the coefficient of variation.

**Table 5.1** Mean (SD) cross-correlation values and time-lags (in samples) between the iPod and stand-alone accelerometer signals.

| | | Walk | Walk DT | Stand EO | Stand EC | Stand DT | Semi EO | Semi EC | Semi DT |
|---|---|---|---|---|---|---|---|---|---|
| Cross-correlation values | AP | 0.90 (0.07) | 0.90 (0.05) | 0.90 (0.06) | 0.92 (0.04) | 0.90 (0.05) | 0.88 (0.07) | 0.89 (0.07) | 0.88 (0.06) |
| | ML | 0.93 (0.03) | 0.93 (0.03) | 0.92 (0.03) | 0.93 (0.03) | 0.93 (0.02) | 0.93 (0.02) | 0.94 (0.02) | 0.93 (0.03) |
| Time-lag (samples) | AP | 34 (7.9) | 36 (10.1) | 30 (6.0) | 31 (6.8) | 33 (13.5) | 32 (5.4) | 32 (6.2) | 37 (19.8) |
| | ML | 35 (7.1) | 36 (10.0) | 30 (5.9) | 31 (6.7) | 34 (13.5) | 32 (5.3) | 32 (6.1) | 37 (19.8) |

1 sample is 0.01 s
Anterior-posterior (AP) and medio-lateral (ML) directions for walking without dual task (Walk), with dual task (Walk DT), while standing parallel (Stand) and semi-tandem (Semi) with eyes open (EO), eyes closed (EC) and while performing a dual task (DT)

**Table 5.2** The validity of the iPod compared with the stand-alone accelerometer for walking without (Walk) and with dual task (Walk DT) and the test-retest reliability of the iPod during Walk expressed in the intra-class correlation coefficient [95% confidence interval] for the index of harmonicity (IH) and amplitude variability (VarAmp) in anterior-posterior (AP) and medio-lateral (ML) plane.

| Condition | N | Intra-class correlation coefficient [95% confidence interval] | | | |
|---|---|---|---|---|---|
| | | IH AP | IH ML | VarAmp AP | VarAmp ML |
| Validity | | | | | |
| Walk | 59 | 0.85 [0.76-0.91] | 0.90 [0.83-0.94] | 0.87 [0.79-0.92] | 0.96 [0.93-0.98] |
| Walk DT | 59 | 0.93 [0.88-0.96] | 0.94 [0.90-0.96] | 0.92 [0.87-0.95] | 0.98 [0.96-0.99] |
| Reliability | | | | | |
| Walk | 57 | 0.88 [0.78-0.93] | 0.87 [0.77-0.93] | 0.97 [0.90-0.99] | 0.97 [0.87-0.99] |

All ICC values were significant ($p<0.05$)

### ***Posture parameters***

Fifty-seven participants completed all standing conditions. Two participants were not able to maintain the semi-tandem stance with eyes closed for one minute and one participant did not perform the semi-tandem with dual task according to protocol. Those three trials, all of participants in the older adult category, were excluded from the analysis.

The cross-correlation values between the iPod and the accelerometer unit signals were ≥ 0.88 for the AP and ML directions in all standing conditions. The mean time lag was between the 0.3-0.4 s (see Table 5.1).

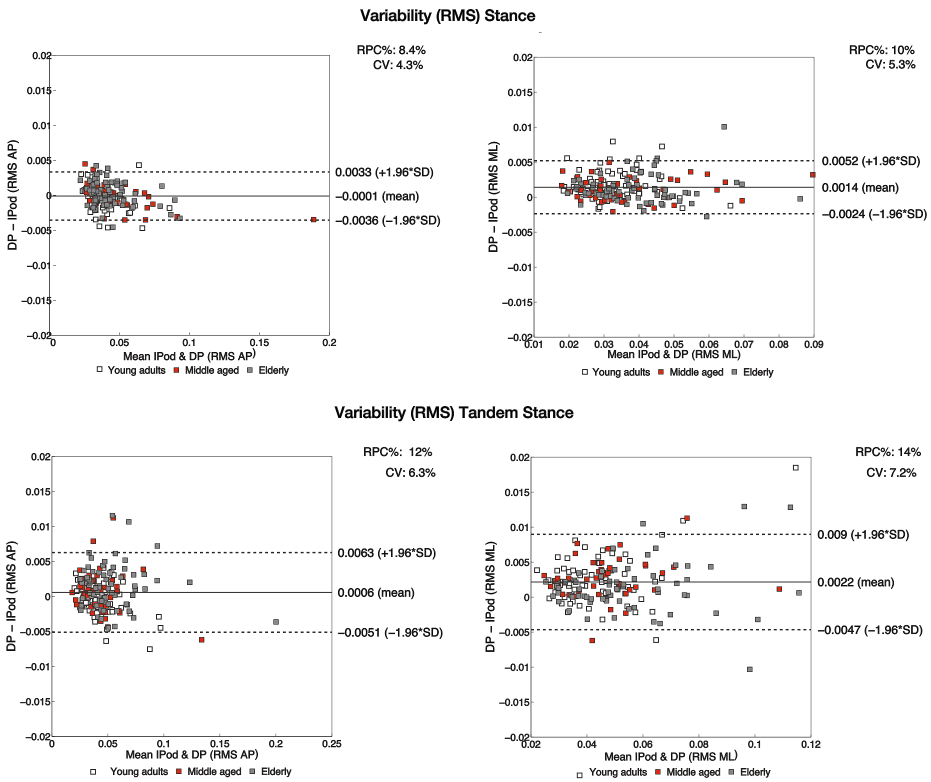



**Figure 5.4** Bland-Altman plots of the mean of the measurements of the iPod and the stand-alone accelerometer (Acc.Unit; x-axis) against the difference of the measurement of individual participants, for the RMS value of anterior-posterior (AP) and medio-lateral (ML) accelerations during parallel standing and semi-tandem stance. White squares represent young adults, red the middle aged adults, and grey the older adults. RPC% is the reproducibility coefficient as % of the mean. CV is the coefficient of variation.

As shown in Figure 5.4, Bland Altman plots showed very good levels of agreement for the RMS values between the two measurement devices. Almost all RMS values of both standing tasks are within the limits of agreement. Individual spread of measurements was larger for ML RMS than AP RMS. For tandem stance, more values of participants in the older adults' category fell beyond the limits of agreement.

Bland Altman plots of the MPF (Figure 5.5) showed that the majority of the values are within the limits of agreement. However, the spread of the values was larger for MPF than for RMS values, in particularly of the participants in the young adult category, as quantified by a higher reproducibility coefficient expressed as percentage of the mean percentage (RMS RPC%, <15%, and MPF RPC% between 32% - 45%).

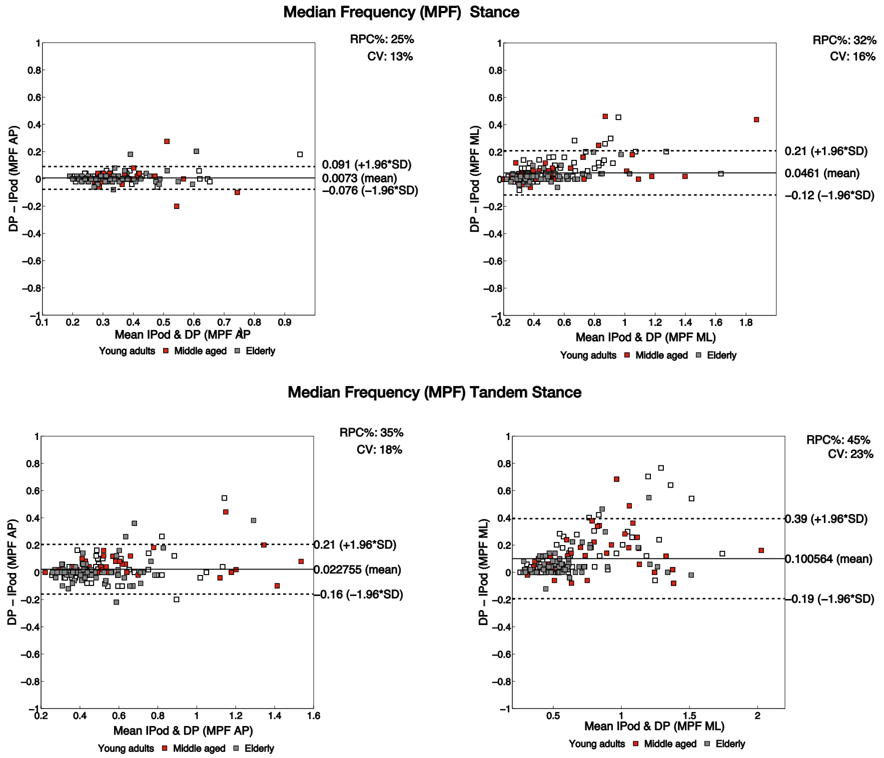



**Figure 5.5** Bland-Altman plots of the mean of the measurements of the iPod and the stand-alone accelerometer (Acc. Unit; x-axis) against the difference of the measurement of individual participants, for the median power frequency (MPF) value of anterior-posterior (AP) and medio-lateral (ML) accelerations during parallel standing and semi-tandem stance. White squares represent young adults, red, middle aged adults, and grey the older adults. RPC% is the reproducibility coefficient as % of the mean. CV is the coefficient of variation.

5

SA measurement had small limits of agreement, however, as is shown in Figure 5.6 in both conditions one subject falls far beyond the limits of agreement increasing the SD and the RPC% values.

Table 5.3 gives an overview of the ICC values and confidence intervals per condition and the reliable ICC values for the three age categories. The ICC values, to assess the validity of the iPod during standing, were ≥ 0.97 for the RMS and the SA. The MPF had ICC values between 0.84 and 0.97. Separate analysis for the age categories revealed no differences in validity, ICC's for the MPF ranged from 0.85-0.97 and for the RMS from 0.97-1.00, respectively.

ICC values for the test-retest reliability of AP and ML RMS during parallel stance and semi-tandem stance were between 0.83 and 0.90. The MPF had values ≥ 0.78 except for the parallel stance with eyes open in AP direction for which an ICC value of 0.59 was found. The individual MPF ICC values for the age groups differed during parallel stance, the ICC values for the young, middle aged and older adults were respectively, 0.39, 0.78 and 0.62 for AP, and 0.86, 0.25 and 0.70 for ML.

Overall, the ICC for the test-retest reliability of SA was 0.81 in the parallel stance and 0.91 in the semi-tandem stance. At group level, the young adult category had lower ICC values on the SA parameter in both parallel standing and semi-tandem stance (respectively, ICC values of 0.57 and 0.55), compared to the other two groups (Table 5.3).

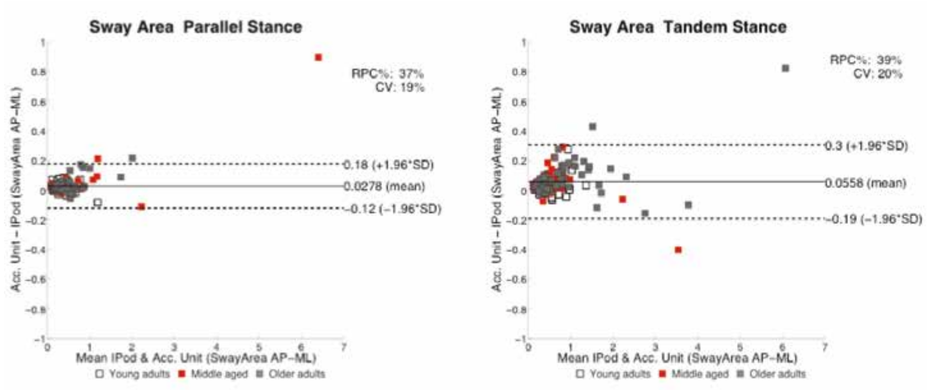



**Figure 5.6** Bland-Altman plots of the mean of the measurements of the iPod and the accelerometer unit (Acc. Unit; x-axis) against the difference of the measurement of individual participants, for the sway area in anteriorposterior (AP) and medio-lateral (ML) plane during standing and tandem stance. White squares represent young adults, red, middle aged adults, and grey the older adults. RPC% is the reproducibility coefficient as % of the mean. CV is the coefficient of variation.

**Table 5.3** The validity of the iPod compared with the DynaPort and the test-retest reliability of the iPod expressed in the intra-class correlation coefficient with a 95% confidence interval for the standing tasks for the root mean square (RMS) and median power frequency (MPF) in anterior-posterior (AP) and medio-lateral (ML) directions and the Sway Area.

| Condition | N | Intra-class correlation coefficient [95% confidence interval] | | | | |
|---|---|---|---|---|---|---|
| | | RMS AP | RMS ML | MPF AP | MPF ML | Sway Area |
| Validity | | | | | | |
| Stand EO | 60 | 0.99 [0.98-0.99] | 0.98 [0.97-0.99] | 0.85 [0.75-0.90] | 0.95 [0.92-0.97] | 0.99 [0.98-0.99] |
| Stand EC | 60 | 0.99 [0.99-1.00] | 0.99 [0.98-0.99] | 0.97 [0.94-0.98] | 0.96 [0.93-0.97] | 0.99 [0.99-1.00] |
| Stand DT | 60 | 1.00 [0.99-1.00] | 0.99 [0.98-0.99] | 0.92 [0.87-0.95] | 0.94 [0.91-0.97] | 0.99 [0.98-0.99] |
| Semi EO | 60 | 0.98 [0.97-0.99] | 0.96 [0.94-0.98] | 0.90 [0.84-0.94] | 0.86 [0.78-0.92] | 0.98 [0.97-0.99] |
| Semi EC | 58 | 0.98 [0.97-0.99] | 0.97 [0.96-0.98] | 0.95 [0.91-0.97] | 0.84 [0.74-0.90] | 0.97 [0.95-0.98] |
| Semi DT | 59 | 0.99 [0.99-1.00] | 0.98 [0.97-0.99] | 0.93 [0.89-0.96] | 0.93 [0.88-0.95] | 0.99 [0.98-0.99] |
| Reliability | | | | | | |
| Stand EO | 60 | 0.83 [0.73-0.90] | 0.90 [0.83-0.94] | 0.59 [0.32-0.75] | 0.78 [0.63-0.87] | 0.81 [0.68-0.89] |
| Young | 22 | 0.86 [0.66-0.94] | 0.74 [0.39-0.89] | 0.39 [-0.36-0.74]* | 0.86 [0.66-0.94] | 0.57 [-0.04-0.82]* |
| Middle | 15 | 0.95 [0.84-0.98] | 0.93 [0.79-0.98] | 0.78 [0.34-0.93] | 0.25 [-0.61-0.72]* | 0.90 [0.69-0.80] |
| Older | 23 | 0.70 [0.31-0.87] | 0.91 [0.79-0.96] | 0.62 [0.12-0.84] | 0.70 [0.31-0.87] | 0.80 [0.53-0.91] |
| Semi EO | 60 | 0.88 [0.80-0.93] | 0.86 [0.77-0.92] | 0.82 [0.70-0.89] | 0.87 [0.79-0.92] | 0.91 [0.85-0.95] |
| Young | 22 | 0.80 [0.49-0.92] | 0.74 [0.38-0.89] | 0.77 [0.45-0.90] | 0.92 [0.81-0.97] | 0.55 [0.00-0.81] |
| Middle | 15 | 0.96 [0.88-0.99] | 0.92 [0.78-0.97] | 0.89 [0.68-0.96] | 0.81 [0.46-0.94] | 0.95 [0.86-0.98] |
| Older | 23 | 0.84 [0.62-0.93] | 0.89 [0.73-0.95] | 0.55 [-0.02-0.81] | 0.85 [0.64-0.93] | 0.94 [0.86-0.98] |

Parallel stance (Stand), semi-tandem stance (Semi), under eyes open (EO), eyes closed (EC) and dual task (DT) conditions
Young (aged 18-35, N=22), Middle (aged 36-55, N=15) and Older (aged 56-75, N=23) healthy adults, *Not significant

## Discussion

The aim of the present study was to establish the validity and test-retest reliability of the iPod Touch in quantifying gait and standing postural control under different conditions (eyes open, eyes closed and dual task) in healthy adults divided into three age categories (young, middle aged and older adults). We compared different acceleration signal characteristics of the iPod Touch with those of a stand-alone accelerometer unit considered as the golden standard. For the walking condition the pattern of the raw signals, the FC detection, the frequency content indexed by the IH and the VarAmp were assessed. Similarly, for the posture task, the pattern of the acceleration signals were compared using cross-correlation analysis, the variability in the signal was calculated by the RMS, the frequency content estimated by the MPF and the amplitude of the sway acceleration using a sway area measure in the AP ML plane.

The cross-correlation values indicated a very similar signal pattern of the two devices for all subjects, and task conditions. A short time delay was found, due to the fact that both devices did not start at exactly the same time.

For walking a FC detection algorithm was compared between the two devices, because many step related gait parameters such as the mean stride time, the coefficient of variation of stride time and gait symmetry indexes, rely on FC detection. In the present study, we used a validated algorithm [26] with the differences that instead of the maximum peak of the AP acceleration the minima of the AP peak within a step cycle was determined. The differences between detected peaks of the iPod and the accelerometer unit was negligible small only 0.02 seconds (2 samples), and thus can be considered valid.

The IH and VarAmp, representing the smoothness of the acceleration pattern and the variability in gait cycles during walking respectively, were valid and reliable outcome parameters measured with the iPod during walking under both single and dual task conditions. This is in agreement with a previous study reporting good validity and reliability for gait measured under single task condition with a smartphone in a group of young healthy subjects [20]. Furthermore, our study showed that the iPod has valid and reliable results in young, middle aged and older healthy adults. The outliers in the Bland-Altman plots for IH and VarAmp were originative from two participants. The two participants represented the two lowest individual cross-correlation values (respectively 0.51 and 0.57). Although it was not observed and reported during the measurements, the low cross-correlations and consequently the outliers in the Bland-Altman plots, indicated that there was a lose fixation of the iPod and stand-alone accelerometer to the participant's lower back.

The posture parameters (RMS, MPF and SA) were valid for all six standing conditions and for the three age categories. Although the limits of agreement were small for all variables, the Bland Altman plot showed outliers in the parallel stance and semi-tandem stance in the SA parameter. Those outliers were recorded during the dual task condition, the participants were laughing during the trial causing the aberrant values. Both the iPod and the commercial unit registered the outlier, underlining the validity of the iPod.

The test-retest reliability for the RMS and SA in the two standing conditions was good. However, the reliability on the MPF was lower. Additionally, the individual age groups showed large differences on the ICC values for the MPF in AP and ML planes during parallel stance and in AP in semi-tandem stance. This might be due to the signal/noise ratio during the postural task. The trunk movements are quite small during standing, and although we filtered the data, noise within the frequency range of the movement can influence the outcomes of the parameters, particular the outcomes in the power spectrum [27]. Unfortunately, this type of noise cannot be removed by filters because accelerations related to the movement of the participant will be removed too [19]. The results of the present study indicate that for the test-retest reliability more repeated measurements are needed to obtain reliable estimates for postural control parameters.

The SA parameter seemed high reliable for the middle aged and older adults, whereas young adults showed lower test-retest reliability (Table 5.3). A possible explanation might be the variation in the young participants balance strategy across the testing session due to the easy level of the stances and therefore performing more variable movements. In contrast, when the tasks are more challenging for instance for persons with movement pathology, the standing task might be performed with less variability. In line with this thought studies in stroke patients and low back pain patients showed a higher reliability in more challenging standing conditions (eyes-closed condition) compared to an easier condition (eyes-open condition) [28,29].

The iPod Touch used in the present study was fixed near the lower back around L3. Placement at the lower back is frequently used to determine gait and postural parameters due to the location near the body's center mass [30,26]. Motions of the body's center of mass are detected and strike patterns of both feet are obtained. However, future research should investigate whether placement of smart devices on other places than the lower back obtains valid and reliable outcome parameters during gait and postural tasks.

Overall, the results showed that trunk accelerations in AP and ML planes measured with an iPod Touch during gait and postural tasks were accurately measured in young, middle aged and older healthy adults under different sensory and dual-task conditions. The gait and posture parameters derived from the iPod acceleration signals were demonstrated to be valid and reliable. Further work will include patient populations, frail elderly and old adults with an increased fall risk to assess the accuracy of smart devices in those populations.

The iPod Touch is a convenient, easy to use, cost-effective device to assess AP and ML trunk accelerations during gait and posture. To make the use of smart devices accessible for clinical practice, applications need to be developed for gait and posture testing including algorithms not only for data recording and storage but also for data analysis, providing feedback to the person or clinician about gait and posture function. With the use of the tri-axis accelerometer embedded in a smart device and apps with algorithms to evaluate gait and postural control specifically developed for different end users, clinicians and researchers can accurately monitor gait and postural control to detect fall risk or evaluate the effectiveness of an intervention to improve gait and/or posture. To develop successful applications, gait and postural parameters need to be determined that are specific and sensitive to changes in aging to develop reliable and sensible applications for the clinical setting.

***Acknowledgements***

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# CHAPTER 6

# Multiple gait parameters derived from iPod accelerometry predict age-related gait changes

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## Abstract

**Introduction**
Normative data of how natural aging affects gait can serve as a frame of reference for changes in gait dynamics due to pathologies. Therefore, the present study aims 1) to identify gait variables sensitive to age-related changes in gait over the adult life span using the iPod and 2) to assess if these variables accurately distinguish young (aged 18-45) from healthy older (aged 46-75) adults.

**Methods**
Trunk accelerations were recorded with an iPod Touch in 59 healthy adults during three minutes of overground walking. Gait variables included gait speed and accelerometry-based gait variables (stride, amplitude, frequency, and trajectory-related variables) in the anterior-posterior (AP) and medio-lateral (ML) directions. Multivariate partial least square analysis (PLS) identified variables sensitive to age-related differences in gait. To classify young and old adults, a PLS-discriminant analysis (PLS-DA) was used to test the accuracy of these variables.

**Results**
The PLS model explained 42% of variation in age. Influential variables were: mean stride time, phase variability index, root mean square, stride variability, AP sample entropy and ML maximal Lyaponov exponent. PLS-DA classified 83% of the participants correctly with a sensitivity of 83% and specificity of 71%.

**Discussion**
Contrary to the frequently reported high gait variability observed in old adults with frailty and fall history, the present study showed that younger compared with older healthy adults had a more variable, less predictable and more symmetrical gait pattern. A model based on a combination of variables reflecting gait dynamics, could distinguish healthy younger adults from older adults.

## Introduction

Natural aging and pathological conditions modify gait. Age-related declines in muscle strength, mass, quality, and neural activation produce characteristic modifications in the kinematics, kinetics, and energetics of gait [1–3]. Although age-related changes in neuromuscular function are well documented [4], less is known about how gait changes across the adult lifespan [5,6]. Identifying subtle changes in gait from young adulthood to old age could provide an objective basis for clinicians to prescribe interventions and delay the onset of mobility disability.

Wearable technologies seem to revolutionize gait analysis. Smart devices, like smartphones and iPods, are equipped with built-in accelerometers, which offers new opportunities for clinicians and researchers to easily and relatively inexpensively record and characterize gait in detail [7,8]. Data extracted from accelerometers worn on the trunk allow the identification of foot contacts from anterior-posterior (AP) accelerations; such data can serve as a basis for sophisticated stride analyses [9]. Additional processing of the amplitude and frequency content of trunk acceleration signals can be used to characterize dynamic balance control during gait through metrics such as self-affinity, regularity, and local stability of the trunk [10,11]. There is increasing evidence suggesting that these variability-related and stability-related gait variables can distinguish the difference in gait patterns of healthy young adults and old adults, old adults with and old adults without cognitive disorders and fallers and non-fallers [12–14] and complement information provided by gait speed alone [15].

Even though accelerometry-based gait analysis generates a wealth of information, most studies focus on one or two characteristics of the acceleration signal (e.g., stride-related parameters: stride time, stride time variability). Such an approach makes it difficult to comprehensively examine the inter-relationship between variables that could reveal additional dimensions of gait. A detailed characterization of the relationship between gait outcomes on the one hand and the association of these variables with age on the other hand, could provide a better understanding of how natural aging affects gait. To this aim, we pursued two complementary objectives. The first objective determined the relationship between different gait variables and the association of these variables with age. The second objective quantified the discriminative power of the identified gait variables to distinguish younger from older adults. Our strategy was to complement commonly used gait variables (i.e., gait speed, stride time) with gait outcomes that reflect the dynamic characteristics of gait, with respect to variability and local stability. To identify the sensitive gait variables across the lifetime and determine the discriminative power of these variables, we used an unbiased, blind approach with no a-priori assumptions about the gait variables that could be most important with respect to aging. We used a Partial Least Square analysis (PLS) and PLS-discriminant analysis for the analyses.

## Methods

### *Participants*

We recruited 59 healthy adults from the community in the age range of 18 to 75 (mean age: 45 (18); 47% male). The participants included in the young group had a mean age of 28 (7) years (age range 19-41; n=29; 59% male) and in the older group the mean age was 62 (8) years (age range 47-74; n=30; 33% male). Participants were included if they were free of orthopaedic and neurological conditions and used no medications that might affect gait. This study was part of a project designed to analyse gait and balance by smart devices (iPod Touch) [7].

The Ethical Committee of the Center of Human Movement Sciences at the University Medical Center Groningen approved the research protocol and all participants signed written informed consent.

### *Gait assessment*

Each participant walked back and forth along a 10-m long course with a one-meter wide curve at the two turns for three minutes at a self-selected habitual speed, a total of two times. Gait variables obtained in the first trial were included in dataset 1 to build a model. Variables obtained in the second trial were included in dataset 2 for validation of this model. Mean gait speed was computed based on the distance covered during the three-minute test.

Trunk accelerations were measured during walking with an iPod touch G4 (iOS 6, Apple Inc.; sample frequency 88-92 Hz) affixed to the trunk with an elastic belt near the level of lumbar segment L3. A custom-made application 'iMoveDetection' was installed on the iPod to collect and store the accelerometer data from the built-in tri-axial accelerometer [7].

Anterior-posterior (AP) and medio-lateral (ML) accelerations were analysed using custom-made software in MATLAB (version 2012b, The MathWorks Inc., Natick, MA, USA). Acceleration data were interpolated to a constant sampling rate of 100 Hz. The data were detrended and filtered (Butterworth filter, 4th order; cut-off frequency 20 Hz). Outliers caused by the turns in the walking track were removed from the data using a median filter [16].

To derive stride-related variables, foot contacts were determined from the AP accelerations. Negative peaks were detected in the smoothed signal (Butterworth filter, 4th order; cut-off frequency 5 Hz) to determine foot contacts, which were used to determine stride time [9]. The mean and the coefficient of variation (CV) of stride times was calculated for each participant. Furthermore, the phase variability index (PVI) representing the relative time between successive contralateral foot contacts was determined as:

$$P_i = \frac{FCR_{t(i)} - FCL_{t(i)}}{FCL_{t(i)} - FCL_{t(i+1)}} \times 360°$$

FCL and FCR are respectively the left and right foot contact at time t(i). The PVI is calculated from the variability of the relative phases around 180° using circular statistics. Lower values indicate gait symmetry and more consistent timing [17].

The magnitude of ML and AP trunk accelerations was indexed by the root mean squares (RMS) [18]. The variability of the stride acceleration amplitude (VarAccAmp) was determined by normalizing the data (100 point per stride), superimposing all strides and calculating the average of the point-by-point standard deviations [18].

The index of Harmonicity (IH) represents the smoothness of the AP and ML accelerations. By a discrete Fourier transformation the power spectrum of the accelerations was estimated and the peak power of the first subsequent 10 harmonics was determined. The power spectral densities (PSD) were normalized by dividing the power by the sum of the total power spectrum[19]. The IH was defined as:

$$\mathrm{IH} = \frac{P_1}{\sum_{i=1}^{10} P_i}$$

$P_1$ is the cumulative sum of the PSD of the fundamental frequency, divided by the first 10 super-harmonics $\Sigma P_i$. PSD of each peak was calculated within frequency bands of +0.1 and −0.1. An IH of 1 indicates a harmonic smooth gait pattern.

Detrended Fluctuations Analysis (DFA), Sample Entropy (SEn) and the maximal Lyapunov exponent ($\lambda_{max}$) were calculated. The DFA quantified long-range correlations in stride time intervals, revealing the predictability of future fluctuations by past fluctuations. Stride time data were divided into windows of equal length $n$ ($n$= N/7, N = signal length) ranging from 17-25 for the individual participant. In each window a linear trend line was fitted and the average fluctuation F($n$) around the line was calculated. The slope of the fitted line in log F($n$) versus log $n$ is the estimated scaling exponent α. The presence of long-term correlations in the signal is indicated by values $0.5 \geq \alpha \geq 1$. A value closer to 1 represents a more correlated pattern. Large and small values of the time-series are likely to alternate when $\alpha < 0.5$ [20].

The SEn AP and ML represent the predictability of the gait pattern. The SEn is the negative natural logarithm of the conditional probability of epochs of length $m$ ($m$=2 in this study) that match point-wise, repeating itself for $m$+1 points within a tolerance of $r$ ($r$=0.1). Smaller SEn values are associated with greater predictability of acceleration patterns [21].

The $\lambda_{max}$ of ML and AP accelerations, quantifying the ability to resist small perturbations during walking, is a measure of local stability. Gait trajectories, corresponding to the gait cycles, were constructed in a state space. The log of the expansion or contraction of the Euclidean distance between the gait trajectories quantified $\lambda_{max}$. The $\lambda_{max}$ was estimated with the method of Wolf using an embedding of 10 dimensions with 7 samples time delay. A larger $\lambda_{max}$ represents greater sensitivity to local perturbations [22].

### *Statistical analyses*

We modeled the relationship between 15 gait variables and age using Partial Least Squares (PLS) analysis. This analysis accounts for the inter-dependency between gait variables. PLS analysis is appropriate to handle a large set of independent variables, low number of observations, and multi-collinearity among variables [23]. With PLS analysis, the internal structure among gait variables (X-matrix) best modeling age (Y-matrix) was identified. The data were pre-processed by a log-transformation and a z-transformation. The optimal number of latent factors is determined by adding latent factors until the predicted residual sum of squares (PRESS) decreases. The amount of variance of the gait variables explained by the models latent factors indicates the relevance of the variables in the prediction of age. A gait variable is considered completely relevant if its modeling power is 100% and less relevant if the modeling power is around 13% (latent factor/number of gait variables). Note that a variable without variation can be fully explained by the model, while this variable might not predict age. Therefore, the Variable Importance in Projection (VIP) quantifies the importance of each individual variable in the final model. Variables with a VIP value >1 are considered very important in explaining age, whereas variables with a VIP<0.8 have less influence on the model [23]. The score and weight plots of the PLS model illustrate the relationship between participant's age and gait variables, with respect to the individual latent factors. The scores summarize the gait variables values for individual participants, from which age can be predicted. The weights present the importance of gait variables in association with age for the individual latent factors.

The PLS model was evaluated by the goodness-of-fit and the goodness-of-prediction. The goodness-of-fit describes how well the model fits the gait variables (dataset 1) in relation to age. The goodness-of-prediction represents the capacity of the PLS model to predict the correct age from the gait variables in dataset 2.

To examine if the gait variables identified as important in the PLS model (VIP>0.8) would discriminate between younger (aged 18-45) and older (aged 46-75) adults, a PLS-discriminant analysis (PLS-DA) was performed. A Receiver Operating Characteristic (ROC) curve based on the PLS-DA was constructed; considering the true positive rate (sensitivity) and false positive rate (specificity) of the discriminating model. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a threshold. The threshold determines the optimal boundary between younger and older adults in the classification. The area under the ROC curve (AUC) is an indicator of the model performance: the closer AUC is to 1, the better the accuracy of the classification [24].

The PLS analysis were performed using the PLS_toolbox for MATLAB (version 3.7.8; Eigenvector Research Inc., Wenatchee, WA, USA).

## Results

### *Relationship between gait variables versus age*

The PLS model, consisting of 2 latent factors, explained 42% of the variance in age (Y-matrix) and 42% of the variance in the gait variables (X-matrix). Although gait speed was slightly different between the two walking trials (0.05 m/s), the goodness-of-fit (based on dataset 1) and the goodness-of-prediction (based on dataset 2) both had a value of 0.42. The first latent factor captured the variance of the variables related to the amplitude of the acceleration signal, the $\lambda_{max}$ AP and gait speed. Two stride-related variables (mean stride time and PVI), frequency-related variables and the SEn AP were highly relevant for the second latent factor (Table 6.1). The gait variables with a VIP>1.0 that were highly associated with age, were mean stride time, RMS ML, $\lambda_{max}$ ML, VarAccAmp ML, VarAccAmp AP and SEn AP (Table 6.1). Although, IH, $\lambda_{max}$ AP and gait speed captured variance in the latent factors, these variables were less important in the prediction of age (VIP<0.8).

Figure 6.1 illustrates the relationship between gait variables and the association with age for the latent factors. The position of participants in a given direction in Figure 6.1A is influenced by gait variables lying in the same direction in the weight plot, Figure 6.1B. The age continuum in Figure 6.1A spans from the lower left (young) to the upper right (old) quadrant. Higher values of the gait variables in Figure 6.1B in the left lower quadrant were associated with a lower age (respectively, mean stride time, RMS AP, RMS ML, VarAccAmp AP, VarAccAmp ML, $\lambda_{max}$ ML, SEn AP) and higher values of the variables in the upper right quadrant with a higher age (PVI).

### *Discriminating model*

A PLS-DA model was constructed to determine the discriminative power of the identified gait variables of the PLS model (VIP>0.8) to distinguish younger (aged 18-45) from older adults (aged 46-75). The discriminant analysis was performed with the following variables: mean stride time, PVI, RMS AP and ML, VarAccAmp AP and ML, SEn AP and $\lambda_{max}$ ML.

Figure 6.2 shows the ROC curve for the PLS-DA model. The AUC was 0.83 (95% confidence interval: 0.72-0.93), i.e., the PLS-DA model identified 83% of the participants correctly. With an optimal threshold at 0.50, the sensitivity and specificity were respectively 83% and 71%.

**Table 6.1** Presentation of the mean (SD) values obtained on the gait variables and the variance captured by each latent factor (LF) for the gait variables in the PLS model. The explained variance in gait variables (X) and age/age group (Y) per latent factor is presented in the last rows.

| **Gait variables** | **Healthy adults** | | **Variance Captured (%) PLS model** | | | **VIP value** |
|---|---|---|---|---|---|---|
| | **Younger** | **Older** | **LF 1** | **LF 2** | **Total** | |
| *Stride-related variables* | | | | | | |
| Mean stride time (s) | 1.1 (0.08) | 1.1 (0.08) | 0 | 29 | 29 | 1.41 |
| CV of stride time | 3.3 (1.45) | 3.4 (1.94) | 3 | 0 | 3 | 0.04 |
| DFA | 0.7 (0.17) | 0.7 (0.15) | 0 | 6 | 7 | 0.04 |
| Phase variability index | 7.8 (2.17) | 8.8 (2.14) | 3 | 24 | 27 | 0.92 |
| *Amplitude-related variables* | | | | | | |
| RMS AP | 1.9 (0.42) | 1.8 (0.37) | 43 | 8 | 51 | 0.90 |
| RMS ML | 1.9 (0.47) | 1.6 (0.43) | 69 | 4 | 73 | 2.07 |
| VarAccAmp AP | 0.9 (0.32) | 0.7 (0.19) | 80 | 11 | 91 | 1.27 |
| VarAccAmp ML | 1.2 (0.34) | 1.0 (0.25) | 87 | 5 | 92 | 2.78 |
| *Frequency-related variables* | | | | | | |
| IH AP | 0.9 (0.08) | 0.9 (0.08) | 9 | 44 | 52 | 0.50 |
| IH ML | 0.9 (0.08) | 0.9 (0.08) | 13 | 37 | 50 | 0.27 |
| *Trajectory-related variables* | | | | | | |
| SEn AP | 1.2 (0.20) | 1.1 (0.19) | 4 | 52 | 55 | 2.55 |
| SEn ML | 1.6 (0.12) | 1.6 (0.16) | 1 | 3 | 4 | 0.48 |
| $\lambda_{max}$ AP | 0.3 (0.32) | 0.3 (0.21) | 22 | 12 | 34 | 0.29 |
| $\lambda_{max}$ ML | 1.1 (0.64) | 0.8 (0.39) | 11 | 0 | 11 | 1.08 |
| *Additional gait variables* | | | | | | |
| Gait speed (m/s) | 1.2 (0.14) | 1.2 (0.11) | 34 | 11 | 45 | 0.39 |
| **Explained X-variance (%)** | | | 25 | 16 | 42 | |
| **Explained Y-variance (%)** | | | 28 | 14 | 42 | |

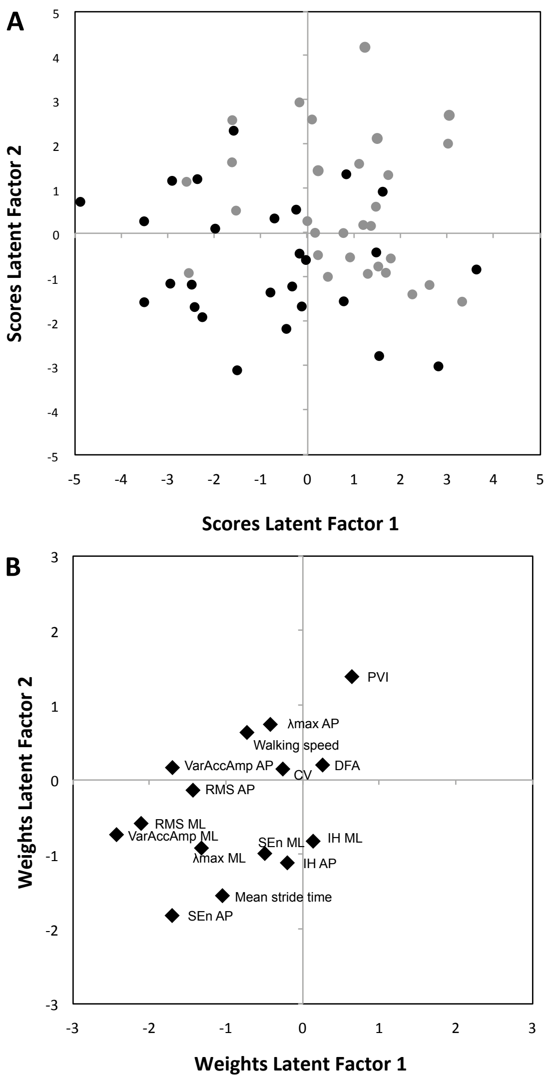


**Figure 6.1** Score plot (**A**) shows the relationship between the participants and their similarities/dissimilarities with respect to age on the two latent factors. Participants aged >45 are displayed in grey and those aged ≤45 in black. Coupled to the weight plot (**B**), the inter-relatedness among the gait variables and age is revealed.

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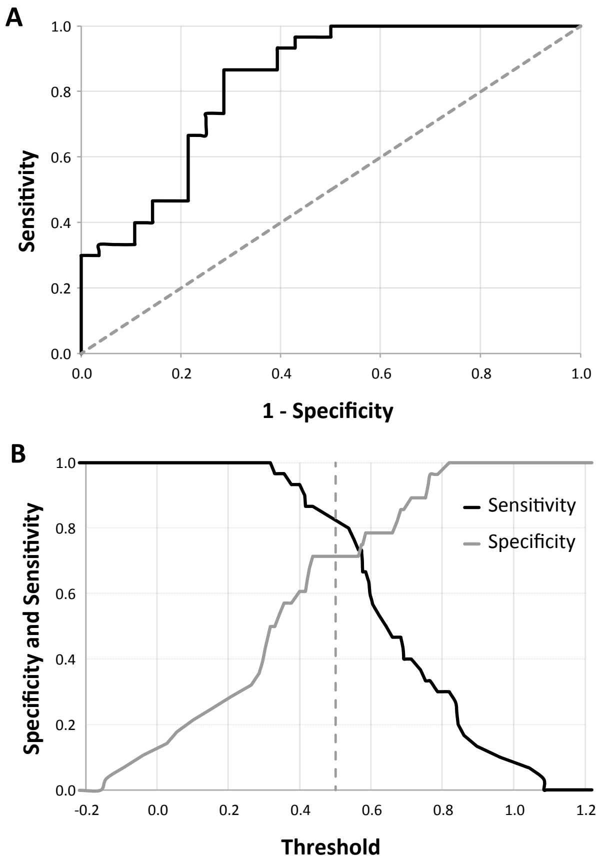


**Figure 6.2** Sensitivity plotted against 1-specificity for all cut-off values of the PLS-DA model in the ROC curve (**A**). To determine the optimal cut-off point, sensitivity and specificity are plotted against the threshold (**B**), the optimal cut-off point is present at 0.50.

## Discussion

We addressed two complementary objectives. First, we identified gait variables that were sensitive to age-related changes. Secondly, we determined the discriminative power of gait variables identified in step one, to distinguish younger (aged 18-45) from older adults (aged 46-75). We constructed two models: a PLS and PLS-DA. The PLS analysis showed that the gait pattern of younger compared to older adults was characterized by a larger mean stride time and a more variable but less predictable and regular trunk acceleration pattern. Additionally, older adults' gait patterns were less symmetrical as indicated by the larger PVI. The PLS-DA model based on the gait variables associated with age in the PLS model had a classification accuracy of 0.83, with a sensitivity of 83% and specificity of 71% to discriminate older adults from younger adults.

The PLS model identified that gait variables related to the amplitude of the accelerations accurately predicted age, as indicated by high VIP values and strong weights. Younger compared with older adults had a higher RMS and exhibited higher variability of between strides acceleration amplitude, suggesting that the RMS, a commonly used variable in gait analysis [25,26], is one of the important predictor of age. Additionally, as reported previously, younger vs. older adults had a longer mean stride time and more symmetrical steps [13,14]. The stride-related variables, mean stride time and PVI, supplemented with SEn AP and and $\lambda_{max}$ ML were also associated with changes related to age. These variables were effective to discriminate between younger and older adults.

Interestingly, younger vs. older adults had a more variable, less predictable gait pattern. These results are in contrast to the frequently reported higher step/stride variability observed in old adults with and without frailty and fall history [5,14]. The increase in local stability and predictability of the gait of older adults presumably reflects a gait pattern consisting of short steps and low step symmetry [27]. The higher variability in trunk acceleration patterns observed in young adults, might indicate that gait variability is not linearly related to age (increasing variability with increasing age), but rather follows a U-shape; healthy young adults positioned on the left side (larger variability), healthy middle/older aged in the middle (lower variability), and frail, high fall risk, and cognitive impaired older adults positioned on the right side (increased variability). Sub-optimal gait patterns can contain too much or too little variability, stability and predictability. Abnormal gait can be characterized by rigidity, inflexibility and high predictability, or, on the contrary, such gait can have elements that are random, unfocused and unpredictable [18]. There is a range in between those two extremes that determines optimal gait. However, for gait variability over the adult life span, this has not yet been modeled. This hypothesis should be examined in future studies using a much larger sample and including frail and cognitive impaired elderly.

Slow gait speed, increased stride CV and IH are outcomes commonly used to characterize age-related differences in gait [13,25,28]. However, our analyses revealed that these variables were not as effective for discriminating younger from older adults. Although reduced gait speed is often a predictor of medical conditions like cognitive impairments [12], Parkinson disease [29] and frailty [10], it may not be sensitive and specific enough to differentiate between different populations and to identify subtle gait changes that occur over the adult lifespan. This is in line with the recent findings of Terrier et al. who reported decreased stability from age 40 onwards, but no decline in gait speed [5]. Further research should investigate the relevance of gait speed, stride CV and IH in relation to the other gait variables in different patient populations.

Despite the moderate goodness-of-fit and goodness-of-prediction values of the obtained model, and the relatively small sample size, the analyses identified the gait variables that were associated with age. This set of variables had a good discriminative power in classifying younger and older adults, i.e. an AUC of 83%. The additional value of gait variables is seen in other classification models. The accuracy of a model predicting future falls in community-dwelling elderly increased from 70% to 82% when gait variables were included [30]. Moreover, a classification model of pre-frail and frail older adults based on gait velocity had an accuracy of 78%, which improved modestly but significantly to 86% when smoothness, regularity and predictability of gait were added [15]. These results emphasize that gait analysis should not only focus on gait speed but should also include measures related to the dynamic metrics of gait. Such a comprehensive approach would increase the accuracy of gait classification, an outcome that can be derived from iPod accelerometry; a convenient, easy to use, and inexpensive gait analysis tool. Normative gait data over the adult life span derived through iPod accelerometry can serve as a frame of reference for pinpointing changes in gait dynamics due to natural and pathological aging.

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6

# CHAPTER 7

# Summary & General discussion

## Summary & General discussion

The objectives of this thesis were to investigate the potential for using technology-based risk assessments for (1) fall risk identification in long-term care residents with dementia; and (2) to determine the changes in gait dynamics due to natural aging. ´Fall prevention´ is the overarching theme linking these two aims to identify situations that can lead to falls for highly vulnerable psychogeriatric patients, and detect deterioration in gait and balance of healthy old adults who might fall later in life. This final chapter summarizes the main findings, discusses the current state of knowledge and clinical implications, and proposes future directions per aim.

## Technology-based fall risk assessment in long-term care residents with dementia

### *Main findings*

Fall prevention is a critical issue in old adults in nursing homes and hospitals. Those adults fall more often than their healthy peers in the community because of physical and cognitive impairments. Fall prevention methods, including mobility training or behavior change interventions, have demonstrated limited success in reducing nursing home falls. Due to recent developments in sensor technology, it seems that monitoring long-term care residents would be a suitable alternative method of fall prevention. **Chapter 2** presents an overview of the effectiveness of wearable and non-wearable sensor technologies to prevent geriatric long-term care residents from falling. Fall rates, fall-related injuries, false alarms, and user experience were examined in twelve studies. Three randomized controlled trials showed no reductions in fall numbers, whereas three before-after studies reported a reduction of 2.4 to 37 falls per 1000 patient days. Although reductions in fall-related injuries up to 77% were reported, the current data are inconsistent and give no convincing evidence that sensors reduce the number of falls or fall-related injuries. Moreover, the number of false alarms (16%) is too high. The percentage of correct alarms should be greater than 90% to maintain full nursing staff attention. The following recommendations were made in Chapter 2 to improve clinical applications of sensor systems: 1) an effective fall prevention sensor system should cover multiple locations 24 h per day and monitor the circumstances in which falls occur; 2) such a system should map individual fall risks and underlying processes and lead to a decision-making model that can predict falls; and 3) sensor manufacturers should involve designers and users in sensor development and fabrication. Chapters 3 and 4 discuss the second and third recommendations.

**Chapter 3** described the fall incidence, fall-related injuries, and fall circumstances for twenty long-term care residents living at a geriatric ward. Eighty-five percent of the long-term care residents fell at least once during the 19 months in which falls were recorded.

A total of 115 falls (5.1 ± 6.7 falls/person/year) occurred, with 28% of falls witnessed by staff or a family member. Nearly one-third of all falls were associated with serious consequences. Two residents died prematurely as a result of hip fractures due to falls; these outcomes underscore the need for effective fall prevention in this population. Using existing data reported by nursing home staff, the relationship between patient characteristics and fall rate in long-term care residents with dementia was assessed to develop a fall risk decision-making model. Sixty-six patient characteristics were extracted from the electronic patient records and classified into seven domains: demographics, activities of daily living, mobility, cognition and behavior, vision and hearing, medical conditions, and medication use. A model was developed to identify the relationships between the sixty-six patient characteristics and fall rate. The results showed that cognitive impairment related to disinhibited behavior, in combination with mobility disability and fall-risk-increasing-drugs (FRIDs), was associated with a high fall rate. In contrast, immobility, heart failure, and the inability to communicate were associated with lower fall rates.

In **Chapter 4** the attitude of health care staff toward fall prevention technologies was examined. Participating staff members came from four closed wards housing long-term care residents with dementia. One of the wards was involved in the development of a new fall prevention system. The available sensor systems in the nursing home were bed-exit alarms and shoe chips. Questionnaire results showed that caregivers considered fall prevention very important. Caregivers were content with available sensor systems because a notification was given when a high (fall) risk situation occurred, but shortcomings were identified in the notification, activation, and availability of sensors. Proposed requirements for a new fall prevention system were: event notification without delay, an automatically activated sensor system, and availability for all residents. Interviews revealed that time, education, and management support were considered as very important factors by health care workers for the successful implementation of a new fall prevention sensor system technology. User involvement appeared crucial for nursing home staff to take part in research and generate willingness to invest in a new fall prevention sensor system.

### ***Sensor requirements in long-term care residents with dementia***

*Sensor type*

Chapters 2 and 4 presented data concerning the effectiveness and the pros and cons of fall prevention sensors currently used in intramural care facilities. It seems that long-term care residents with dementia prefer non-wearable sensors to wearable sensors because cables and patches of wearable sensors might cause obstructive situations which lead to resident agitation and attempts to remove sensors. Although many wearable sensors are applied and hidden within clothes, it is not uncommon that residents with dementia undress themselves several times per day in their confusion, making the sensors useless. Even non-wearable sensors must operate unseen by residents, as residents are often unable to cope with visible devices in their rooms [1,2]. For example, residents can feel threatened by a small active indicator light in their room. Residents will try to turn the light off, thereby making the device non-operational. Furthermore, automatic sensor activation is necessary in long-term care facilities because residents with dementia will be unable to activate a sensor independently [3]. However, sensor activation by staff is not the solution; health care staff often includes temporary employees who are unfamiliar with the available sensors and individual alarm settings. Automatic sensor activation can reduce human errors and false alarms. Thus, non-wearable, invisible and automatically activated sensors should be used for fall prevention in long-term care residents with dementia.

*Sensor network*
Multiple non-wearable sensors could be integrated into an interlinked sensor network. A coupled multi-sensor network provides the opportunity to examine resident characteristics and monitor residents at different locations in the facility. Various sensors and algorithms have been developed to recognize specific human activities and determine deviations from expected patterns [4,5]. Those technologies, among others, are used for fall detection, sleep monitoring, physiological parameter tracking (e.g., heart rate, breathing rate, and gait) and activity estimation [4]. Integrating multiple existing sensors and algorithms makes it possible to detect, classify, and monitor daily activities. The recorded data can be used as input for a fall risk decision-making algorithm to more effectively prevent falls. This will be further discussed in paragraph 7.1.3.

Their small spatial scope limits the operational range of the sensors currently used for fall prevention. Such sensors can 'see' only a small area (Chapter 2). Multiple sensors, interlinked within a network, could cover a larger area and monitor residents in multiple rooms. The broader spatial permits increased resident freedom of movement and assists health care staff in monitoring residents. However, one difficulty in processing data from (multiple) non-wearable sensors is monitoring multiple persons in the same room or residents moving between rooms. If the software is designed to capture only one individual, the presence of multiple people in the same room might cause false alarms or miss situations with risks for a fall [3]. In long-term care facilities, multiple residents will require monitoring and health care staff and visitors will be present in those monitoring areas. Therefore, the software processing the sensor data should distinguish residents from one another, from visitors, and from health care staff by means of a resident recognition algorithm. Sensor systems might lose track of a resident when one person blocks the line of sight to another person or when residents change rooms [3]. Programming an algorithm to recognize residents is a great challenge for future software development.

*Privacy Issues*
Monitoring residents and storage of sensor data entails addressing privacy issues, especially when a camera is integrated in the sensor system. Data of residents, health care staff, and visitors are stored and might identify individuals. Therefore, laws and regulations

concerning the storage and accessibility of the gathered data need to be strictly applied. In The Netherlands, data management should comply with the privacy law ('Wet bescherming persoonsgegevens'). Additionally, the European Commission intends to strengthen and unify data protection for individuals with the General Data Protection Regulation (GDPR), which will be introduced in 2016. Finally, when data is used for research purposes, the Declaration of Helsinki is applicable.

Regulations about data storage and accessibly are strictly formulated. All data needs to be made anonymous prior to storage. The key to identifying individual residents from the coded data must be stored separately, only accessible to select personnel. Collected data should only be used for the goals set prior to data recording to protect the privacy of all people involved. Thus, even those with authorization to access data shall not use the data without a pre-determined purpose [6]. Storing data anonymously and controlling access helps ensure a safe environment for residents, visitors, and staff.

### *A fall risk model in long-term care residents with dementia*

A fall risk profile is the basis for the decision-making algorithm. A decision-making algorithm is the software in a fall prevention sensor system that identifies high fall risk situations. A profile, the 'ground-truth,' based on the normal activity patterns and health status of the resident, is necessary to distinguish deviations from normal situations. By determining fall risk factors and underlying causes for falls, residents with an increased fall risk can be identified. A threshold must be set to sufficiently discriminate between a high fall risk situation and a not-at-fall-risk situation. By comparing the 'ground-truth' with the current state of the resident, unusual behavior and high fall risk situations can be identified.

#### *A static versus dynamic fall risk model*

Chapter 3 presents a model that determined the association between fall rate and patient characteristics. The results showed that the combination of impaired mobility, indicators of disinhibited behavior, diabetes, and use of analgesics, beta blockers, and psycholeptics were associated with falls. Those results already give some useful guidelines for health care staff in clinical practice. Health care staff can specifically address the need for firm and safe footwear for residents. In addition to footwear, regular foot care is important to minimize mobility problems. Furthermore, careful medication prescriptions and frequent updates to medication use and doses can further minimize loss of balance and falls [7–9]. By reviewing medication use regularly, prescriptions can be adjusted to avoid unnecessary and excessive medication use.

Chapter 3 presents a static fall risk model, as the model considers residents' fall risk at one given moment in time. However, given the nature of dementia, with progression of mental state and changes in physical well-being, one might expect residents' 'normal' situation to change over time. Therefore, a dynamic fall risk model is required for a technology-based fall prevention system. The model could be updated and adapted to the medical and physical state of each resident. Adding regular health care measures (e.g., blood pressure and weight) and lab test results (e.g., hydration status, glucose level, and cholesterol) and including up-to-date information about diagnoses, behavioral problems, and actual medication use might improve fall risk model accuracy.

*Adding sensor data to the fall risk model*

Monitoring residents with sensors 24 h per day allows more real-time information about residents' health status and activities. Information about activities, walking abilities, restlessness, and location can be derived from various sensors. When using a camera-based system, silhouettes can be generated to anonymize the visual data, as presented in Figure 7.1 [10]. However, those silhouettes have another purpose: they are useful to determine resident gait abilities. With shape analysis, one can obtain spatiotemporal gait parameters such as stride time, step length, and step width [10–12]. In addition to camera-based systems, sleep mattress sensors are introduced into health care facilities to measure large body movements, heart activity, and respiration efforts [13,14]. Data derived from various sensors should be added to the personalized profiles to determine the current health state of the resident and update the level of fall risk.

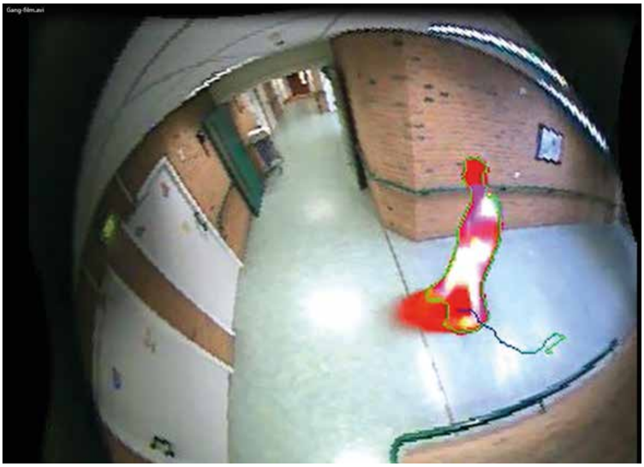

**Figure 7.1** Video monitoring with silhouette generation.

*Personalized and self-learning fall prevention model*

Residents with dementia in long-term care facilities exhibit highly heterogeneous physical and cognitive characteristics. Therefore, an individual approach is mandatory in the development of a smart fall prevention system. The fall risk decision-making model needs to be personalized so that fall risk alarms are accurate and reliable. Personalized models that identify fall risks are highly data intensive: models must collect a large amount of individual data over extended periods of time and perform on-line self-updates. The model would incorporate new event information detected automatically or entered by an operator and would re-train itself using self-learning strategies to aid in current and individual fall risk decision-making [3].

### *User requirements for a fall prevention system*

Developing and implementing technologies successfully into practice requires involvement of both designers and users. A recent review addressed the underrepresentation of user acceptance, ease of use, business models, and privacy in technology development [5]. These factors are strong indicators of how well the technology will eventually be accepted by users and the market [5,15]. However, with the introduction of more and more technology into clinical settings, awareness of the importance of user involvement is increasing. Depending on the setting and the device that is developed, users might be residents, family members, or health care staff. In our fall prevention project, the users were the health care staff of the long-term care facility, as described in Chapter 4.

The International Organization for Standardization (ISO) presented an overview of the activities that are recommended in user-centered designs, in the ISO 9241-210. The standard includes the following six principles of a user-centered design: (1) understanding the context of use (e.g., users, tasks, environment); (2) active involvement of users in design and development; (3) user-centered evaluation of the design; (4) iterative process; (5) evaluation of user experience (e.g., perceptual and emotional aspects); and (6) the design team includes multidisciplinary skills and perspectives [16]. Applying those principles in designing new sensor technologies is expected to reduce the risk for developing systems that will not be used, or used less than intended. Additionally, a user-centered design might enhance the work quality, reduce support and training costs, and improve user satisfaction because the technologies are based largely on wishes and demands of the users. Ultimately, users determine whether or not a sensor system will be successfully used; thus, user involvement in technology development is crucial.

### *Development of a fall prevention system*

*Sensor introduction in long-term care facilities*

The first recommendation of Chapter 2 was to use non-wearable sensors that monitor residents' activities 24 h per day under a variety of living conditions and at multiple locations. We introduced two cameras and a sensor mattress into our psychogeriatric intervention ward, monitoring one bedroom and the hallway with the bedroom door. The videos protected privacy by silhouetting the images (Figure 7.1) and allowed us to characterize walking ability afterwards. The bed in the monitored room was equipped with the sensor mattress (Emfit bed sensor mat, Emfit Ltd, Finland)), measuring movements, respiration, and heart activity. We were mainly interested in the events and resident status prior to the fall. In total, four falls were captured, including two falls due to unbalanced standing in the hallway, one due to a wet floor near the bed, and one due to unbalanced rocking in bed (presented in Figure 7.2). Although the number of falls recorded was not large enough to allow any statements about the situation prior to a fall, the data do indicate that a variety of circumstances is associated with fall incidents.

**Figure 7.2** Fall due to unbalanced rocking in bed.

*Spin-off monitoring system*

The smart fall prevention system proposed by the INTERREG IV A project (Chapter 1, Page 13), is not yet available. However, by combining multiple existing sensors with decision-making algorithms recognizing a pre-fall situation, a smart fall prevention system might be realized in the near future. As a spin-off of the project, two involved companies (AVICS and DYSI) have developed the smart optical sensor (SOS; http://www.avics.nl/domotica/slimme-optische-sensor-sos). This device is able to detect restlessness in bed, movement outside the bed, residents leaving the room to visit the bathroom, inactivity (fall detection), and the presence of other persons in the room (to avoid false alarms). The sensor is placed at the ceiling and the alarm threshold is adjusted to the personal needs of the resident. Although the SOS does not prevent residents from falling, a quick detection of a fall incident might prevent the consequences of a prolonged lie after a fall. Those consequences include: hospitalization, dehydration, hypothermia, pneumonia, and death [5,17]. When, in the future, an algorithm is developed to detect high fall risk situations, such an algorithm could be integrated into the SOS software to extend the device features.

### *Future directions in the development of a smart fall prevention system*

Based on the information presented in this thesis, we surmise that a smart fall prevention system should have the following properties, to prevent residents with dementia in a long-term care facility from falling:

- Multiple, non-wearable, invisible, and automatically activated sensors, integrated into an interlinked network. The system operates by an algorithm that can identify activities and recognize individuals. Privacy laws and regulations about data storage and accessibility preserve privacy of residents, visitors, and health care staff.

- The data in this thesis suggest that a dynamic fall risk decision-making model is necessary to identify risk factors for an (impending) fall. The model requires data collected over 24h, supplemented by resident information retrieved from electronic patient files. A self-learning strategy optimizes and personalizes the model.
- Users (health care staff) need to be involved in the development and implementation of any such smart fall prevention system.

In conclusion, using a combination of existing sensors within a coupled sensor network and a personalized fall risk profile might lead to the realization of a smart fall prevention system in the future. Users must be involved during the design and implementation phases of the system and their opinions and needs should be carefully considered. A smart fall prevention system will assist health care staff 24 h per day to prevent resident falls and reduce the number of serious fall-related injuries, thus improving quality of life for this vulnerable group.

## Technology-based gait assessment in healthy adults

### *Main findings*

Gait and balance control change over the life span due to natural aging but also because of neurologic and non-neurologic disorders. Monitoring gait changes over time might enable early identification of balance and mobility impairments. This monitoring offers the possibility to provide timely and personalized interventions to reverse or slow disease progression and health deterioration. Objective assessments using technological devices, such as tri-axial accelerometers, play an important role in quantifying gait and balance abilities. Recently, smart devices such as smart phones and iPods have come equipped with tri-axial accelerometers. This feature provides the opportunity to assess gait and balance in clinical practice with a user-friendly and low-cost device. In **Chapter 5** the validity and reliability of the built-in, tri-axial accelerometer in the iPod Touch was investigated. The iPod Touch was validated in a group of 60 healthy adults aged 18 to 75 years, under different standing and walking conditions. Participant trunk characteristics during gait and balance were measured using an iPod Touch and stand-alone accelerometer while they walked under single- and dual-task conditions, and while standing in parallel and semi-tandem stances with eyes open, eyes closed or while performing a dual task. The anterior-posterior (AP) and medio-lateral (ML) accelerometer signals of the iPod Touch and stand-alone accelerometer were highly correlated. Three different characteristics (time, amplitude, and frequency-related variables) of the accelerometer signal were assessed to determine the validity and reliability of the iPod Touch during walking and standing. The gait variables derived from the signal were the foot contact moments, the amplitude variability, and the index of harmonicity. Standing variables included the sway area, the root mean square of the acceleration signal, and the median power frequency. Overall, the iPod Touch obtained valid and reliable measures of gait and postural control in healthy

young, middle-aged, and older adults under different conditions. This finding highlights the potential of smart devices to be used for clinical gait and posture assessments.
Pursuing a frame of reference for gait changes due to natural aging, various gait variables were derived from the trunk acceleration signal recorded with the iPod Touch during the single walking task in Chapter 5. The gait variables included stride, amplitude, frequency, and trajectory-related variables based on the AP and ML acceleration signals. Furthermore, gait speed was supplemented. **Chapter 6** described the relationship between gait variables and their relation to age. The gait variables associated with age included mean stride time, phase variability index, root mean square, stride variability, AP sample entropy, and ML maximal Lyaponov exponent. More specifically, younger adults walked with a higher mean stride time and with more variability but less stability than older adults, whereas older adults walked with a less symmetrical gait pattern compared to younger adults. Additionally, the discriminative ability of the gait variables associated with age was examined. This combination of gait variables associated with age accurately classified younger (ages 18 to 45) and older (ages 46 to 75) adults. Normative data of how natural aging affects gait can serve as a frame of reference for gait dynamics changes due to pathological aging.

### *Validity and reliability of smart devices*
Objective assessments using technological devices play an important role in gait and balance quantification. The advent of smart devices with built-in, tri-axial accelerometers allows for an easy and accurate way to assess gait and balance abilities in clinical and community settings. Several studies have validated the built-in, tri-axial accelerometer in smart devices during walking and standing; results have been reported as reliable and accurate [18–20]. The data presented in Chapter 5 underscored those results and provided new insights about the use of smart devices for adults aged 18 to 75 years under different standing and walking conditions. Using the iPod Touch, reliable and valid results were obtained for the different aspects of the accelerometer signal (e.g., time, amplitude, and frequency domains).

Smart devices are increasingly used for research purposes (e.g., gait ability assessment in patients with rheumatoid arthritis and Parkinson's disease) [19,21,22]. In addition to using smart devices in research, it is important to introduce smart devices in clinical settings to assess balance and gait. Smart devices are low-cost and user-friendly compared to standard assessment devices (e.g., Optotrak systems, stand-alone accelerometers); thus, objective gait and balance assessments are more accessible for clinicians.

### *Gait variables associated with age*
*Gait variables sensitive to aging*
Multiple gait variables can be derived from trunk acceleration signals, representing different gait pattern characteristics. Step and stride variables, based on foot contacts (peaks) identified in the AP trunk acceleration signal, for example, are frequently used in

gait assessments [23–27]. Although acceleration signals provide a wealth of information, including information about variability, smoothness, predictability, and stability of gait, only a small set of variables representing those characteristics is included in studies [28,29]. Additionally, the sophisticated analyses needed to obtain gait variables and interpret the trunk acceleration signal present a major barrier for clinicians to use accelerometers in clinical settings. However, to determine specific gait changes due to aging, different gait characteristics should be considered. A combination of multiple gait variables sensitive to age-related changes provides more insight into age-related gait changes than a single variable. Age-related changes in individual gait variables appear small, as presented in Chapter 6. However, a combination of gait variables based on different accelerometer signal characteristics was sensitive to age-related changes. Specifically, younger adults walked with a higher mean stride time and with more variability but less stability compared to older adults, whereas older adults walked with a less symmetrical gait pattern compared to younger adults.

Interestingly, the published literature frequently reports higher gait variability in old adults and frail elderly persons compared with young adults [30,31,28], and more locally unstable gait in old adults and fallers [32,33]. It is well known that gait variability is higher in children compared with healthy adults [31,34]. Children use variability to explore and optimize their walking ability; gait variability decreases steeply during the first period of life [31]. It has been suggested that healthy and adaptable gait relies on the achievement of optimal variability, stability, and predictability. Non-optimal gait patterns can be characterized by too much or too little variability, stability, or predictability. Abnormal gait may be characterized by rigidity, inflexibility, and high predictability (as with Parkinson's disease [35]) or random, unfocused, and unpredictable (as with Huntington's disease [36]). However, there is a range between those two extremes that determines optimal gait. Thus, both low and high variability can characterize a safe gait pattern in healthy adults [25]. Variability of movement patterns has been linked to stability, flexibility, and predictability of movements and is related to task requirements [37]. Variability is necessary to maintain balance; adapting movements while walking leads to greater stability [25]. Healthy gait is characterized by 'organized' variability, whereas disease is defined by loss of complexity, increased regularity, decreased stability, and either increased or decreased variability, depending on the patient group and the task to be performed [38]. Although we proposed in Chapter 6 that a graph of gait variability over time creates U-shape, this has not yet been modeled over the adult life span. Most studies include distinct groups, such as healthy older adults vs. frail or cognitively impaired elderly, or fallers vs. non-fallers. Hardly any reference data exist with respect to variability, stability, and predictability of gait patterns over the adult lifespan. Further research should investigate the pattern of gait variability over the lifespan to more specifically define healthy variability and unhealthy variability in relationship to stability, flexibility and predictability.

*Classification algorithms*

Aging and health-related problems affect multiple gait variables; therefore, a reference frame based on multiple variables is necessary. The gait variables sensitive for age presented in Chapter 6 had good discriminatory ability to classify younger and older adults. The next step is to create a frame of reference, including normative values for natural aging, to recognize subtle changes which indicate unusual gait and balance characteristics. However, to further improve the classification model and obtain a reference model for gait ability, the number of participants over all ages should be expanded. Furthermore, reference data should be obtained for healthy adults older than 75, for less healthy old adults (e.g., frail elderly, fallers), and patients with various disease states (e.g., Parkinson's disease, diabetes, multiple sclerosis). Algorithms can be developed based on reference data to distinguish healthy adults from fallers, frail elderly, adults with cognitive impairments, and patients with particular diseases.

***Gait and balance assessment applications in clinical settings***

Smart devices are increasingly used for research purposes, especially to gather and store data [18–20,39]. However, data processing and data analysis are still performed on laptops or computers with sophisticated software; this software requirement is a major barrier for clinicians to perform gait and balance assessments in clinical settings. Therefore, prior to the implementation of smart devices as gait and balance assessment instruments in clinical settings, applications (apps) are required to collect data, process data, and identify gait and balance characteristics [40]. An app is a piece of software that can be installed on a smart device. Apps are designed for a specific task or contain a certain set of information. Apps to assess gait and balance can be developed for diagnostic, monitoring, or intervention purposes.

*Diagnostics*

A quick, objective, and easy-to-use gait and balance assessment device could provide disease identification prior to symptom revelation. Interventions could start early to slow or reverse disease consequences. The gait variable most often associated with aging, falling, diseases, and even mortality, is reduced gait speed [41]. In distinct groups (younger vs. older adults, healthy adults vs. adults with medical conditions), gait speed seems to be a discriminating variable [30,42,43]. However, our analysis in Chapter 6 did not mark gait speed as a sensitive measure for natural aging. Gait speed might be sensitive for disease-related changes, but it is not specific in determining the underlying cause of the reduced speed. Accelerometer-based assessments are sensitive and specific for measuring gait and balance ability [44–46]. Detecting deviations from the natural gait pattern by assessing multiple gait variables might identify the underlying disease state cause of gait changes such as a preliminary stage of Parkinson's disease or Alzheimer's disease. Normative data are required about natural, age-related changes, but also about changes in gait and balance due to deteriorating health and diseases. Smart devices could be used for diagnostic purposes when a reference frame with normative gait and balance performance values is available. Gait and balance assessments with a smart device are easy and quick to perform: only a few minutes are needed to set up and complete the task.

*Monitoring*

The effectiveness of an intervention or the progression of a disease can be (home-) monitored with smart devices. Almost 80% of the Dutch population owns a smartphone, and this number is increasing, especially among those aged 65 years and older [47]. Due to the wide availability of smart devices in the general population, these devices can be used as self-assessment tools. Gait and balance characteristics can be monitored over a longer time period to detect subtle changes, with data collection occurring every week or for a certain period of time. The monitored person does not have to visit a physician for routine check-ups because the apps are accurately monitoring the patient's situation. A patient may receive a warning to visit a physician for a medical check or the physician would receive a notification when changes occur.

*Intervention*

Gait and balance intervention programs can be provided with smart devices [23]. Facilitating long-term gait and balance training at home could reduce hospitalizations and physiotherapist visits. Based on patient trunk movements, real-time feedback on motor performance can be provided to help improve gait or balance performance. Casamassima et al. (2014) used a smartphone and an inertial sensor to improve gait in patients with Parkinson's disease using real-time feedback [23]. Instructions were sent to patients to execute the most effective gait pattern, based on real-time computation of gait characteristics. For example, one of the gait characteristics monitored was gait symmetry. When asymmetry was detected, the instruction content included 'increase right/left step length'. Providing real-time feedback during walking or standing will help to improve or maintain mobility in old adults.

*Additional smart device measures*

The gait and balance information can be combined with other patient monitoring applications such as diabetes management and medication adherence apps [48]. Information about sleep rhythm, activity patterns, and heart rate can be added. Integrating multiple health-related outcomes provides the opportunity to monitor people more closely without frequent physician visits. Changes preceding events or disease evolution can be detected early and intervention can occur at an early stage.

There are a few commercial apps currently available to collect the measured acceleration signals from smart devices. However, these applications do not yet process the data to provide comprehensible information to the user about gait and balance performance. The introduction of such an app will probably only be a matter of time with the fast evolving developments in the field of technology and application use. App developers will have to take into account the required input data, the algorithms to process the data, and the presentation of results to the user.

***Future directions in technology-based gait and balance assessment***

In view of the results of the present thesis, we consider the following aspects necessary to realize a low-cost, user-friendly, and objective gait and balance assessment in clinical settings:

- The combination of gait variables that is sensitive to age-related changes, as identified in Chapter 5, needs to be examined in a larger study, including more healthy adults and adults older than 75. To make a better distinction between healthy and unhealthy variability in relationship to stability, flexibility, and predictability, the pattern of gait variability over the entire lifespan should be investigated.
- Normative data are required for natural, age-related changes, but also for the changes in gait and balance due to deteriorating health and disease states. Classification algorithms can be based on those reference frames to distinguish healthy adults from adults with physical or cognitive impairments.
- Applications (apps) are necessary to implement gait and balance assessments into clinical settings. An app is needed to collect and process the data, identify gait and balance characteristics and present the results in a way the user (physician or patient) understands. Apps can be developed for diagnostic, monitoring, or intervention purposes.

In conclusion, smart devices can be used as objective gait and balance assessment instruments. Normative data of how natural aging affects gait can serve as a frame of reference for changes produced by aging coupled with disease. The next step is to develop (commercial) applications that collect and process gait and balance data to distinguish normal from abnormal gait characteristics. In the near future, old adults might be able to monitor their gait and balance ability by self-assessment at home. Physicians are then informed about the health status of patients without regular visits. Personalized training targeting gait and balance capacities can then be provided to maintain or improve the mobility of this population.

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# Nederlandse samenvatting
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# Nederlandse samenvatting

De term ‘gezond ouder worden’ verwijst naar het behouden van fysieke en cognitieve gezondheid, het vermijden van ziekten en beperkingen en actief en onafhankelijk blijven. Helaas is dit niet vanzelfsprekend voor de 3 miljoen 65-plussers in Nederland. Het natuurlijke verouderingsproces wordt geassocieerd met een achteruitgang van fysiek en cognitief functioneren en heeft ernstige gevolgen voor mobiliteit, vergroot het risico om te vallen, beïnvloedt kwaliteit van leven, zorgafhankelijkheid en sterfelijkheid. Het zo lang mogelijk behouden van onafhankelijkheid en kwaliteit van leven is essentieel voor ouderen, hun familie en verzorgers. Onder het mom ‘voorkomen is beter dan genezen’ is een gevarieerd aanbod aan preventie methoden beschikbaar om fysiek en cognitief functioneren te behouden. Preventie strategieën kunnen worden verdeeld in twee benaderingen:

1) preventie door middel van real-time monitoring om situaties met een hoog risico te detecteren en een signaal te geven voor onmiddellijke zorg;
2) preventie door middel van een langdurige interventie, zoals bewegingstrainingen, het herzien van medicatievoorschriften en educatieve programma’s.

Echter, voordat een geschikte (val)preventiemethode geïmplementeerd kan worden, is het noodzakelijk om te bepalen of een individu een verhoogd risico heeft op mobiliteitsverlies of om te vallen. Technologische oplossingen kunnen mogelijk bijdragen aan meer effectieve en individuele preventie omdat ze de mogelijkheid hebben om kleine maar essentiële veranderingen te detecteren voorafgaand aan het manifesteren van mobiliteitsproblemen of een val.

‘Valpreventie met behulp van sensortechnologie’ is het overkoepelende thema in dit proefschrift dat de twee onderzoeksdoelen aan elkaar verbindt. Ten eerste is er onderzocht wat de potentie is van het gebruik van sensortechnologie voor het identificeren van valrisico’s bij verpleeghuisbewoners met dementie. Ten tweede is onderzocht of het mogelijk is om veranderingen te detecteren in loopvaardigheden als gevolg van natuurlijke veroudering, bij gezonde ouderen die later in hun leven kunnen vallen.

***Het valrisico bepalen van psychogeriatrische patiënten met behulp van technologie***

Valpreventie is een belangrijk onderwerp voor ouderen in verpleeghuizen en ziekenhuizen. Deze ouderen vallen vaker dan hun zelfstandig wonende leeftijdsgenoten omdat ze fysieke en cognitieve problemen hebben. Valpreventiemethoden, zoals mobiliteitstrainingen of gedrag veranderende interventies, laten beperkte successen zien in het reduceren van vallen in verpleeghuizen. Door recente ontwikkelingen met betrekking tot sensortechnologie lijkt het erop dat het monitoren van verpleeghuisbewoners met sensoren een passende methode zou kunnen zijn om vallen te voorkomen. In het eerste deel van dit proefschrift zijn de eerste stappen genomen voor het ontwikkelen van een sensorsysteem dat vallen kan voorkomen bij verpleeghuisbewoners met dementie. In Hoofdstuk 2 is een overzicht gepresenteerd van de effectiviteit van draagbare en niet-draagbare sensortechnologieën om vallen in geriatrische ziekenhuispatiënten en verpleeghuisbewoners te voorkomen. Het aantal vallen, val gerelateerde verwondingen, valse alarmen en de behoeften van de gebruikers (verpleging) werden onderzocht in twaalf studies. Drie randomized controlled trials lieten geen afname zien in het aantal vallen. Daarentegen rapporteerden drie 'voor-na studies' een afname van 2,4 tot 37 vallen per 1000 patiëntdagen. Hoewel er ook een afname van val gerelateerde verwondingen tot wel 77% werd gerapporteerd, is de huidige literatuur inconsistent over de effectiviteit van valpreventie met sensortechnologieën. Er is geen overtuigend bewijs dat sensoren het aantal vallen en val gerelateerde verwondingen doet afnemen. Verder werd een te hoog aantal valse alarmmeldingen (16%) genoteerd. Het percentage van correcte alarmmeldingen moet hoger zijn dan 90% om de volledige aandacht van de gebruikers (verpleging) te houden. Aan de hand van de resultaten uit Hoofdstuk 2 werden de volgende aanbevelingen gegeven om de klinische toepasbaarheid van sensorsystemen te verbeteren:

1) een effectief valpreventiesensorsysteem zou meerdere ruimtes 24 uur per dag moeten overzien en de omstandigheden waarin de vallen plaats vinden, moeten monitoren;
2) een valpreventiesysteem moet in kaart brengen welke individuele valrisico's en onderliggende processen ten grondslag liggen aan een val, dit zou kunnen leiden tot een beslissingsmodel dat vallen kan voorspellen;
3) fabrikanten zouden ontwerpers en gebruikers moeten betrekken in het ontwikkelen en fabriceren van sensoren.

In Hoofdstuk 3 en 4 worden de tweede en derde aanbeveling besproken.

Hoofdstuk 3 beschrijft het aantal vallen, val gerelateerde verwondingen en de omstandigheden waarin de vallen plaats vonden van twintig verpleeghuisbewoners op één geriatrische afdeling. Vijfentachtig procent van de bewoners viel minstens één keer in de 19 maanden van de onderzoeksperiode. In totaal vonden er 115 vallen plaats (5.1±6.7 vallen/persoon/jaar), waarvan 28% werd gezien door een verzorgende of een familielid. Bijna één-derde van de vallen had ernstige gevolgen, waarbij twee bewoners vroegtijdig overleden als gevolg van een heup fractuur. Deze uitkomsten benadrukken de noodzaak voor effectieve valpreventie in deze populatie. Met behulp van de gegevens gerapporteerd door de verzorgenden, werd de relatie tussen patiëntkarakteristieken en het aantal vallen in psychogeriatrische patiënten onderzocht. Dit om uiteindelijk een beslismodel te kunnen maken om het risico op een val te bepalen. Zesenzestig patiëntkarakteristieken werden uit het elektronisch patiëntendossier gehaald en geclassificeerd in zeven domeinen: demografische gegevens, activiteiten van het dagelijks leven, mobiliteit, cognitie en gedrag, visueel en auditief vermogen, medische conditie en medicatie gebruik. Een model werd ontwikkeld om de relatie tussen de zesenzestig patiëntkarakteristieken en de associatie met het aantal vallen te identificeren. De resultaten laten zien dat cognitieve problemen gerelateerd aan ongeremd gedrag, in combinatie met mobiliteitsproblemen en valrisico verhogende medicatie (FRIDs), werden geassocieerd met veel vallen. Anderzijds kwam naar voren dat immobiliteit, hartfalen, en het onvermogen te communiceren geassocieerd werden met weinig vallen. Bewoners behorende tot deze laatste groep zitten en/of liggen voornamelijk en zijn nauwelijks nog mobiel waardoor ze weinig vallen.

In Hoofdstuk 4 is de houding van verzorgenden ten opzichte van valpreventietechnologieen onderzocht. De verzorgenden zijn per slot van rekening de gebruikers van deze systemen. De verzorgenden van vier gesloten psychogeriatrische afdelingen van één verpleeghuis namen deel aan het onderzoek, waarbij één van de afdelingen betrokken was bij het ontwikkelen van een nieuw valpreventiesysteem. De beschikbare systemen in het verpleeghuis bestonden uit bed- en schoensensoren. Resultaten van een vragenlijst lieten zien dat verzorgenden valpreventie erg belangrijk vonden. Ze waren tevreden met de beschikbare sensoren omdat deze een notificatie gaven wanneer een situatie met een hoog (val) risico zich voordeed. Aangewezen benodigdheden voor een nieuw valpreventiesysteem waren: notificaties zonder vertraging, een automatisch geactiveerd sensorsysteem en het beschikbaar zijn van het systeem voor alle bewoners. Verder maakten interviews met verzorgenden duidelijk dat tijd, educatie en support van het management werden gezien als erg belangrijke factoren voor een succesvolle introductie van een nieuw valpreventie systeem. Gebruik maken van het concept ‘users as designers’, bleek cruciaal om deel te willen nemen aan ons gebruikersonderzoek (invullen vragenlijst) en de bereidheid om te willen investeren in een nieuw valpreventiesysteem.

Uit het eerste deel van dit proefschrift kan worden opgemaakt dat het gebruik van verschillende bestaande sensoren - gekoppeld binnen een sensornetwerk en gecombineerd met een persoonlijk valrisicoprofiel - mogelijk kan leiden tot de realisatie van een slim valpreventiesysteem in de toekomst. Gebruikers moeten betrokken zijn bij het ontwerpen en introduceren van het system. Hun mening en behoeften dienen te worden meegenomen in het gehele proces om de preventiemethode te doen slagen. Een slim valpreventiesysteem zal verzorgenden 24 uur per dag ondersteunen bij het voorkomen van vallen en het terugbrengen van het aantal val gerelateerde verwondingen. Daarmee zal de kwaliteit van leven in deze kwetsbare groep ouderen verbeteren.

***Loop- en balansvaardigheid van gezonde volwassenen bepalen met behulp van technologie***

Loop- en balansvaardigheden veranderen gedurende het leven door natuurlijke veroudering maar ook door neurologische en niet-neurologische aandoeningen. Het monitoren van veranderingen in het looppatroon over de tijd zou het vroegtijdig identificeren van balans en mobiliteitsproblemen mogelijk kunnen maken. Daardoor zou er al vroegtijdig een gepersonaliseerde interventie uitgevoerd kunnen worden om gezondheidsafname en/of ziektevoortgang te stoppen of af te remmen. Objectieve metingen met instrumenten zoals versnellingsmeters, spelen een belangrijke rol in het kwantificeren van loop- en balansvaardigheden. Deze instrumenten zijn echter vaak alleen te gebruiken door speciaal opgeleid personeel. Smart devices zoals smartphones en iPods hebben tegenwoordig een ingebouwde versnellingsmeter. Dit geeft de mogelijkheid om loop- en balansvaardigheden in de praktijk te onderzoeken met een gebruiksvriendelijk en relatief goedkoop instrument. In Hoofdstuk 5 is de validiteit en betrouwbaarheid van de versnellingsmeter in de iPod Touch onderzocht. De iPod Touch werd gevalideerd onder verschillende loop- en sta-condities in een groep van 60 volwassenen tussen de 18 en 75 jaar. De rompversnellingen tijdens de loop- en sta-taken werden gemeten met een iPod Touch en een commerciële versnellingsmeter. De looptrial bestond uit 3 minuten lopen tweemaal zonder en eenmaal met dubbeltaak. De sta-trial bestond uit taken van één minuut staan in parallel stand en semi-tandem stand met ogen open, ogen dicht en met een dubbeltaak. De anterior-posterior (AP) en medio-laterale (ML) versnellingssignalen van de iPod Touch en de commerciële versnellingsmeter hadden een hoge correlatie. Drie verschillende karakteristieken (tijd, amplitude en frequentie gerelateerde variabelen) van het versnellingssignaal werden onderzocht om de validiteit en betrouwbaarheid van de iPod Touch te bepalen tijdens lopen en staan. De loopvariabelen afgeleid van het versnellingssignaal waren de voet-contactmomenten, de amplitudevariabiliteit en de “index of harmonicity”. De balans-variabelen waren de “sway area”, de “root mean square” van het versnellingssignaal en de “median power frequency”. De resultaten lieten zien dat variabelen afgeleid van de versnellingsmeter in de iPod Touch betrouwbaar de loop- en balansvaardigheden van gezonde jongeren, volwassenen en ouderen onder verschillende condities kunnen meten. Deze bevindingen benadrukken de potentie van smart devices om te worden gebruikt voor loop- en balansonderzoek in de klinische praktijk.

Om een referentiekader voor veranderingen in het looppatroon door natuurlijke veroudering te definiëren, werden verschillende loopvariabelen afgeleid van het versnellingssignaal opgenomen met de iPod Touch tijdens de looptaak zonder dubbeltaak zoals genoemd in Hoofdstuk 5. De loopvariabelen bevatten schrede, amplitude, frequentie en traject-gerelateerde variabelen gebaseerd op het AP- en ML- versnellingssignaal. Daarnaast werd loopsnelheid toegevoegd. In Hoofdstuk 6 wordt beschreven wat de relatie is tussen verschillende loopvariabelen en de associatie met leeftijd. De loopvariabelen geassocieerd met leeftijd waren: gemiddelde schredetijd, “phase variability index”, “root mean square”, schredevariabiliteit, “AP sample entropy”, en “ML maximale Lyapunov exponent”. Dit betekent dat jongeren lopen met een hogere gemiddelde schredetijd en een meer variabel en onvoorspelbaar looppatroon hebben dan ouderen. Terwijl ouderen een minder symmetrisch looppatroon hebben in vergelijking met jongeren. Aanvullend werd het onderscheidend vermogen van deze variabelen onderzocht. Een combinatie van de loopvariabelen geassocieerd met leeftijd was nauwkeurig in staat om jongeren (leeftijd 18-45) en ouderen (leeftijd 46-75) van elkaar te onderscheiden. Normatieve waarden van natuurlijke veranderingen door veroudering, gebaseerd op de gevonden combinatie van variabelen, kan dienen als referentiekader voor veranderingen in het lopen door pathologische veroudering.

Concluderend: uit het tweede deel van dit proefschrift blijkt dat smart devices kunnen worden gebruikt als objectief meetinstrument voor loop- en balansvaardigheden. Een referentiekader van de veranderingen in het looppatroon als gevolg van natuurlijke veroudering kan worden gebruikt om veranderingen door ziekte te detecteren. De volgende stap is om een (commerciële) applicatie te maken die loopdata verzamelt, analyseert en daarbij een normaal looppatroon kan onderscheiden van een abnormaal looppatroon. In de nabije toekomst, kunnen ouderen misschien zelf hun loop- en balansvaardigheden meten. Artsen worden dan geïnformeerd over de gezondheidsstatus van de patiënt zonder routinematige bezoeken. Indien nodig kunnen gepersonaliseerde trainingen gegeven worden om loop- en balansvaardigheden te verbeteren en vallen en immobiliteit te voorkomen.

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## Curriculum vitae

Nienke Kosse was born on February 28th, 1987 in Hardenberg and grew up in Slagharen, the Netherlands. After finishing high school in 2005 (Vechtdal College, Hardenberg), she started studying Human Movement Sciences at the University of Groningen. During her master, she got involved in research on ´exergaming´ and evaluated an interactive balance training in healthy community-dwelling older adults. After she graduated in 2010, Nienke started with the pre-program of the Master Management, Care and Policy in Gerontology at the University of Brussels in Belgium. Besides her study, she worked as a retail administrator at Delta Lloyd Life in Brussels.

In September 2011 she returned to the University Medical Center Groningen to work on the INTERREG IV A project, 'Telemedicine: Fall prevention' as junior researcher at the Center of Human Movement Sciences. This project was a collaboration between health care institutions, companies and knowledge institutions. In 2014 her research activities were extended with an appointment at the Université Joseph Fourier, France, to investigate the possibilities of smart devices in gait and balance assessment. The results of her research at the University Medical Center Groningen and Université Joseph Fourier are presented in this thesis.

Currently, Nienke works as a researcher at the Sint Maartenskliniek in Nijmegen where she is involved in the research within the orthopedic department. In her spare time she loves to play a game of beach volleyball or ride her bike through the hilly landscape of Gelderland.

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